Appendix 7. Distributions used in Monte-Carlo Simulations

For each of the PRZM3.12 input parameters identified as sensitive by the Plackett-Burman analyses, the nature of the sampling distribution for use in the Monte Carlo uncertainty analysis were defined. Specific criteria were developed for establishing these sampling distributions. These criteria were used to ensure consistency in the procedures for evaluating model prediction error across sites. The criteria also ensured that the sampling distributions represented, to the degree possible, the actual site-specific uncertainty and variation in the parameters. Therefore, the criteria effectively increased the confidence that the Monte Carlo uncertainty analysis results reflect the true model prediction error associated with a specific site and parameter set. In addition, the criteria provided a record against which the sampling distributions were judged. Criteria for input parameter sampling distributions follow:

1. The sampling distributions must explicitly reflect within-site variation of the input parameters. This criterion ensures that intra- and inter-site variation are explicitly identified and any confounding of these types of variation are avoided (unless explicitly stated). For example, it would be inappropriate to have one input parameter distribution reflect within-site variation, and the distribution for a second parameter reflect between-site variation. The interpretation of the Monte Carlo output is difficult with such a parameterization.

   Ideally, the input distribution should represent the range of possible values of the parameter for the explicit application of the model at a specific site. Preferably, actual field measurements of the parameter should be used to establish the distribution. Contributions to the prediction variance of inter-site and inter-chemical components of uncertainty should not be used explicitly to judge model prediction accuracy. However, model runs that incorporate such variance components can be used to test the sensitivity of the model to the largest possible input parameter variance. In fact, incorporating the inter-site and inter-chemical components of variation can be used to evaluate the expected model prediction error with small or non-existent site-specific data sets.

2. The form of the sampling distribution should be consistent between sites for a specific parameter. However, the parameters characterizing the distribution may change. For example, if a normal distribution is chosen for a parameter at one site, then a normal distribution should be used at all other sites. However, the mean and variance of the normal distribution can be site specific.

   This criterion ensures consistency in the interpretation of the Monte Carlo outputs between sites. It also provides a foundation for dealing with sparse data sets for specific parameters at some sites. In many cases, as few as two or three observations of the parameter are available at one site, with more data available at other sites. Therefore, the site with the most data can be used to determine the form of the distribution, with the sufficient statistics calculated on a site-specific basis. In addition, a consistent interpretation of the shape and range of the Monte Carlo outputs between sites requires a consistent use of parameter-specific sampling distributions. The shape of the Monte Carlo prediction distribution is generally a function of the input distributions. The use of consistent input distribution forms allows the shape of the Monte Carlo output distributions between sites to be compared. While the form of the distribution for a specific input parameter did not change between sites, the sufficient statistics of the input parameter, i.e., minimum, maximum, mean etc., were specific for each site. Thus, each distribution was tailored to reflect the specifics of a given site with the underlying assumptions about the nature of the distribution consistent between sites.

3. The form of the distribution should reflect the magnitude, range, and interpretation of the parameter. Many of the input parameters have restricted ranges. For example, application rate cannot be negative. The sampling distribution should reflect the restricted range, with no chance of randomly drawing a negative value. The effect of this criteria is to restrict the use of a normal distribution, and increase the use of uniform, log-normal, beta, and custom distributions (i.e., where random draws of actual measurements substitute for a formal distribution).

In addition, this criterion ensures that the expected site-specific range of a parameter is covered by the selected distribution. It also ensures that values outside the expected range are not overly emphasized. For example, use of uniform distributions over a narrow range may be appropriate when the probability of occurrence of any parameter value is equal over the range.

4. Expert judgment in establishing site-specific distributions is appropriate when little data is available, but a sensitivity test of the choice of distribution is required. For most input parameters, expert judgment is involved in the selection and calibration of the sampling distributions. Sensitivity tests to evaluate changes in the Monte Carlo outputs with choice of distribution were performed.

The following sampling distributions reflect an intensive amount of data collection, evaluation, and discussion among the project team. The distributions reflect site-specific variation only.

1. Chemical Decay Rate (days^{-1}):

Distribution: Beta

Since these are log10 transforms of the DT50 data, the following procedure was employed where the rate constant was set using the following formula:

$k = -\ln(0.5)/(10^{K})$ (K is the sampled value from the beta distribution) (this assumes first-order degradation kinetics)

Georgia #1 Leaching study (GAIL):	alpha = 4.00, beta = 9.92, scale = 3.37 (log10 data)
North Carolina #4 Leaching study (NC4L):	alpha = 4.58, beta = 0.68, scale = 2.75 (log10 data)
Indiana #2 Runoff study (IA2R):	alpha = 2.33, beta = 0.46, scale = 1.53 (log10 data)
Georgia # 2 Runoff study (GA1R):	no data available

Data Source: Registrant chemical specific data package.

2. Rooting Depth (cm):

PRZM has a limitation that the maximum rooting depth cannot be deeper than the total depth of the soil profile. For example, the total soil depth in the IA2R scenario is 91 cm, even though maximum rooting depth for corn can range up to 122 cm, according to the cited references. The MC application does an error check, and if the rooting depth sampled is greater than the soil profile depth, the rooting depth is set to the depth of the soil profile (e.g., to 91 cm in IA2R).

Distribution: uniform

Corn, Midwest:	0.457 - 1.219 m
Corn, Southeast:	0.32 - 0.9 m
Soybeans:	0.65 - 0.90 m

Data Sources: CPIDS; Robertson et al., 1980; Jung and Taylor, 1984; Borst and Thatcher, 1931; Mayaki et al., 1976.

3. Curve Numbers (dimensionless):

Distribution: uniform

GA1R:
fallow: 82 - 88
cropping: 73 - 91
residue: 75 - 81

IA2R:
fallow: 82 - 88
cropping: 45 - 100
residue: 75 - 81

Data Source: Site specific based on measured rainfall and runoff data. PRZM3.12 user manual.

GA1L, NC4L: Not varied.

Data Source: Hydrologic group specific CN values for antecedent moisture condition II, PRZM3.12 user manual.

4. Kd (cm^3/g)

Distribution: uniform

GA1L: 0.25 - 0.36

Data Source: Registrant chemical specific data package. Measured Koc was used to generate a chemical specific regression equation relating Koc and organic carbon to Kd using the equation Kd = Koc* OC/100. The regression equation was then used in a Monte Carlo analysis in conjunction with measured soil organic carbon to generate a distribution of potential Kd values across the site.

NC4L: 0.02 - 0.19

Data Source: Registrant chemical specific data package. Measured Koc was used in a Monte Carlo analysis in conjunction with measured soil organic carbon to generate a distribution of potential Kd values across the site.

IA2R: 18.7 - 208

Note: To set Kd for the lower soil horizons, the following procedure was used:

Koc was calculated from the sample Kd value (Koc(1) = Kd(1)/.0183 -- horizon 1 has 1.83% OC)
Kd(2) = Koc(1)*.0135 (horizon 2 has 1.35% OC)
Kd(3) = Koc(1)*.0093 (horizon 3 has .93% OC)
Kd(4) = Koc(1) *.0057 (horizon 4 has .57% OC)

Data Source: Registrant chemical specific data package. Measured Koc was used in a Monte Carlo analysis in conjunction with measured soil organic carbon (Kd = Koc* OC/100) to generate a distribution of potential Kd values across the site.

GA1R: no site-specific information is available

5. Bulk Density (g/cm3):

Distribution: uniform

Note: The bulk density distributions are depth specific. When models are run at depths that do not match the measured field data, field data associated with the nearest reasonable depth is used to parameterize the model.

GA1R: no data available

Site	Depth (cm)	Range of Bulk Density
IA2R	10	1.10 - 1.19
	30	1.07 - 1.27
	60	1.02 - 1.36
	90	1.09 - 1.28
GA1L	15	1.49 - 1.56
	30	1.49 - 1.60
	45	1.49 - 1.57
	60	1.49 - 1.59
	75	1.54 - 1.59
	90	1.54 - 1.57
	105	1.54 - 1.57
	120	1.54 - 1.57
	135	1.54 - 1.62
	150	1.54 - 1.59
NC4L	0	1.45 - 1.54
	15	1.38 - 1.52
	30	1.42 - 1.53
	45	1.40 - 1.54
	60	1.39 - 1.50
	75	1.40 - 1.43
	90	1.37 - 1.43
	105	1.39 - 1.45
	120	1.41 - 1.49
	135	1.40 - 1.49
	150	1.48 - 1.49
	165	1.45 - 1.48
	180	1.42 - 1.43
	195	1.43 - 1.48
	210	1.46 - 1.54
	225	1.46 - 1.56
	240	1.43 - 1.53
	255	1.43 - 1.47
	270	1.44 - 1.45
	285	1.44 - 1.47
	300	1.45 - 1.46
	315	1.43 - 1.45

Data Source: Registrant chemical specific data packages.

Bulk Density global variability 13 - 16.2% RUSTIC user manual (Dean et al., 1989).

6. Pan Factor (%):

Distribution: uniform

GA1L and GA1R: 75 - 77
IA2R: 71 - 73
NC4L: 75 - 77

Data Source: PRZM3.0 and RUSTIC manuals

7. Application Rate (kg/ha):

Distribution: uniform

NC4L: no site-specific data
GA1L: 0.15 - 0.32
GA1R: 0.15 - 0.26 (actual rate)
IA2R: 0.94 - 2.12

Data Source: Registrant chemical specific data packages.

8. Management Factor (%):

Management factors are taken from Predicting Rainfall Erosion Losses (Wischmeier and Smith, 1978). Each matrix below is crop and crop practice specific. Crop specific USLEC value ranges were selected from those presented by Wischmeier and Smith (1978) to most closely approximate plant growth stages as constrained by PRZM input requirements reflecting fallow, cropping and residue conditions.

Distribution: uniform

GA1R: Annual cotton, conventional moldboard plow and disk

fallow period: 36 - 42
seedbed period: 59 - 68
cropstage 1 (establishment): 59 - 63
cropstage 2 (development): 43 - 49
cropstage 3 (maturing crop): 22 - 44

Based on the GA1R file and its dates for fallow, cropping, and residue, the following values were used.

Date (from Level 2 PRZM input file)	Stage	USLEC range	Notes
1/1	Fallow	36-42	For fallow field, after overwintering of residues
7/3	Cropping	22-44	Late in season, use maturing crop range
11/5	Residue	15-36	

IA2R: Corn after corn in meadow less systems, spring moldboard plow, crop residues left on field

fallow period:	31 - 51
seedbed period:	55 - 68
cropstage 1 (establishment):	48 - 60
cropstage 2 (development):	38 - 45
cropstage 3 (maturing crop):	20 - 33
4L (residue)	23 - 47

Based on the IA2R file and its dates for fallow, cropping, and residue, the following values were used.

Date (from Level 2 PRZM input file)	Stage	USLEC range	Notes
1/1	Fallow	31-51	For fallow field, after overwintering of residues
5/24	Cropping	20-33	Late in season, use maturing crop range
10/10	Residue	23-47	

GA1L: Corn after corn as for GA1R

NC4L: Soybeans after corn, spring moldboard plow, crop residues left on field, plow disk and harrow for seedbed

fallow period:	33 - 45
seedbed period:	60 - 68
cropstage 1 (establishment):	52 - 60
cropstage 2 (development):	38 - 43
cropstage 3 (maturing crop):	17 - 29
cropstate 4 (residue)	9 - 60

Based on the NC4L file and its dates for fallow, cropping, and residue, the following values were used.

Date (from Level 2 PRZM input file)	Stage	USLEC range	Notes
1/1	Fallow	33-45	For fallow field, after overwintering of residues
5/28	Cropping	52-61	Establishment
10/1	Residue	9-60	Cropstage 4

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Appendix 8. Detailed Results of Monte-Carlo Simulations

For the uncertainty analysis, model predictions were compared to actual groundwater or surface water measurements. Model predictions of interest include the following:

Runoff:
- runoff volume (m^3/day)
- sediment yield (kg/day)
- pesticide runoff mass (gm/day)
- pesticide mass in sediment (gm/day)

Groundwater:
- pesticide mass in soil (ug/kg)
- pesticide in pore water (ug/L)
- bromide in pore water (mg/L)

Both graphical and tabular information are presented for comparing the measured field information and model predictions. The ability of the model to predict runoff and leaching factors on a daily basis was evaluated. For the current exercise no attempt was made to scale up the analyses to monthly or yearly comparisons. In addition, no attempt was made to compare results across sites. By using the smallest time-scale available (days), the affect of uncontrolled temporal and spatial influences on the comparison results was reduced. However, the error in model parameterization was incorporated into the comparison through the use of Monte Carlo analysis and generation of a prediction distribution. The prediction distribution represents the uncertainty in model predictions, conditional on the understanding and measurement of the model input parameters. Uncertainty associated with daily field measurements were not included in the analysis. Sources of uncertainty associated with the measured data include the spatial variation within the field site and sample variation, i.e., the variability associated with multiple soil core, soil pore water or runoff measurements and the variability associated with analytical methods. One would anticipate that the variability associated with the former two sources could be considerable while that for the latter would be minimal. In view of the uncertainty associated with the measured data the current analysis is therefore conservative. Allowing for the uncertainty associated with the measured values would increase the correlation of model outcome distributions with distributions representative of the measured data.

Box-and-whisker plots were used to graphically compare measured field information and model predictions. For each day that a field measurement was available, a box-and-whisker plot of the model predictions was overlain on a marker for the value of the field measurement. The box-and-whisker plot displays the lowest, 25th percentile, median, 75th percentile, and maximum value for the model predictions (based on 500 iterations). Examination of the plot shows the relative number of model predictions below and above the measured value, as well as the relationship of the measured value to specific statistics of the prediction distribution (median, 25th percentile, etc.). Model accuracy was evaluated by examining the percent of model predictions below and above the measured value. When the measured field value was shown to be in the general center of the prediction distribution, the model can be considered to be reasonably predictive. When the measured value was seen in the lower or upper portions of the prediction distribution, the model can be considered less accurate (within the bounds of uncertainty) but acceptable given the variability in the model parameters. If the entire prediction distribution is above or below the measured value, then the model may be considered to be inaccurate for that day. However, there are circumstances where this latter scenario does not hold. In particular, for very small measured values (near the level of quantification (LOQ)) the model is frequently shown to predict into the range below the detection level, or only slightly above the detection value. By convention the measured value is always reported as one-half the LOQ. Subsequently, model outcomes that predict below one-half the LOQ may show a disagreement between the measured and predicted values. Practically, however, the model and measured values show good agreement in this case, with the comparison truncated at the limit of quantification. In addition, the model predictions and measured values were frequently found to significantly disagree when the values were above, but very near the LOQ. While the measured and predicted values differ, in many cases the difference is not practically relevant given the small magnitude of the recorded numbers. Measured values near the limit of quantification provide a basis for judging the ability of the model to predict pesticide concentrations at low magnitude.

Tables are provided that show the percent of model predictions (out of 500 iterations) that exceed the measured field value. A one hundred percent exceedence indicates the model predicted high, a zero percent exceedence indicates the model predicted low. Again, the magnitude of the measured values should be used to evaluate the significance of these extreme scenarios.

Runoff

IA2R:

Figure A8-1 presents the Monte Carlo results for site IA2R. Seven days, spanning two years, had measured runoff values. Table A8-1 presents information on the number of predictions exceeding the measured value. For runoff volume, all measured values fell within the interquartile range (between the 25^{th} and 75^{th} percentile of the prediction distribution) of the model predictions, indicating that the model was very reliable. For sediment yield, measured values fell within the interquartile range for three days, within the bounds of the distribution for two days, and outside the bounds of the distribution for two days. For dissolved pesticide runoff mass, five measured values fell within the interquartile range, and the remaining measurements fell within the bounds of the distribution. For pesticide mass in sediment, three measured values fell within the interquartile range of the predictions, three fell within the bounds of the predictions, and one fell outside the bounds of the model predictions.

GA1R:

Pesticide runoff mass was the only value measured at GA1R. Figure A8-2 presents the box-and-whisker plot and Table A8-2 shows the percent exceedence values for the four days on which the measurements were available. For all days, the measured value fell within the interquartile range of the model predictions.

Evaluation of Runoff Prediction Distributions

The nature of the statistical distribution formed by the Monte Carlo predictions (Figure A8-3) was also evaluated. For this evaluation, model predictions distributions were used from IA2R (labeled "input data" in the graphics illustrated in Figure A8-3). The distributions for GA1R were not evaluated, but the results of the analysis using IA2R suggests that the GA1R results would be consistent. Using Crystal Ball® Pro 2000, numerous distributions were fit to the daily model predictions for each of the four runoff output variables. In all cases, the Beta distribution generated by Crystal Ball® Pro fit the model prediction data extremely well (based on goodness-of-fit statistics). This is not surprising because all input distributions used in the analysis were uniform, except for chemical decay rate that was input as a Beta distribution. Since most of the selected input parameters are relatively linear with respect to the model predictions, the shape of the prediction distribution was controlled by the Beta distribution. The parameters of the Beta distribution (shown in Fogure A8-3) can be used to calculate specific areas under the curve of the prediction distribution. These calculations are not presented here, but could be useful in future work.

In the current literature, Monte Carlo prediction distributions generated from exposure models such as PRZM3.12 are used for a variety of purposes. For example, the prediction distribution can be used to assess the probability of exceeding a risk criterion (e.g., an LC50, NOEL, LOEL, IC25, etc). Additionally, the prediction distribution can be used as a basis of comparing model predictions to actual field measurement concentrations (as in this report). Graphically, a relatively accurate calculation of the probability of exceedence can be achieved by examining a graph in which the risk criterion or field measurement is overlain on the predictive distribution. Analytically, the area under the curve to the left or right of the risk criterion can be calculated if the actual form of the distribution is available. In Figure A8-3, the parameters of the Beta distribution can be used to accurately calculate the exceedence probability for the model runs.

This level of accuracy can be useful in some risk assessment applications where the exposure distribution is in close proximity to the actual field measurement or risk criterion.

Given the parameterization of the leaching models presented in this report, it would be anticipated that the prediction distributions for the leaching variables would be Beta as well. Therefore, the results of this analysis were not included in the report.

Days With Zero Runoff Measurements

For the runoff field studies, runoff volume, sediment yield, pesticide runoff mass, and pesticide mass in sediment were monitored continuously for each day of the sampling periods at both the IA2R and GA1R sites. Those days with positive measurements were evaluated in the preceding tables and figures. For all other days, the measured values were assumed to be zero. At issue is whether or not the model can predict zero, or low values, on those days where no runoff, sediment loss, runoff flux, or pesticide mass in sediment were recorded in the field.

Cumulative distributions of the model predictions (over the 500 Monte Carlo iterations) on those days were no runoff volume (Figure A8-4), sediment yield (Figure A8-5), dissolved pesticide runoff mass (Figure A8-6), or pesticide mass adsorbed to sediment (Figure A8-7) were recorded at site IA2R. Table A8-3 presents summary statistics of the information. In particular, Table A8-3 presents the percent of all model predictions that were zero, or greater. In other words, Figures A8-4 through A8-6 and Table A8-3 illustrate the frequency with which the model confirmed the measured values of zero for the four runoff variables. The information provides two conclusions. First, for some days the model clearly predicts positive values for days when the field monitors showed no positive values. For most of these days the model predicted values of small magnitude, near the limit of detection. For a small number of days the model had large positive predictions. Intuitively, these data are not unanticipated given the nature of the Monte Carlo sampling procedure. For each input parameter defined via sensitivity analysis as exerting a significant influence on model outcome, Monte Carlo sampling from a defined distribution would invariably produce a combination of values with a small likelihood of true occurrence. The combination of these input parameters would likely generate a relatively small number of predictions that would occur with low probability. Those low probability input combinations may produce those traces with high positive values (although the cause of these high positive values was not rigorously evaluated). However, overall at least 69% of all model predictions for a specific runoff variable were zero. The highest concordance was seen in the pesticide mass in sediment variable in 1983 where eighty-three percent of the model predictions equaled zero on days where no pesticide mass in sediment was measured.

Figure A8-8 presents the cumulative distribution of Monte Carlo runoff mass values in 1989 at GA1R. Table A8-4 shows that seventy-eight percent of the Monte Carlo predictions were zero.

Leaching

GA1L

Box-and-whisker plots are presented for leaching variables pesticide mass in soil (Figure A8-9), pesticide in pore water (Figure A8-10), and bromide in pore water (Figure A8-11). Percent exceedence calculations for GA1L are presented in Tables A8-5 through A8-10.

Of the forty-three pesticide mass in soil values in year 1, 27 fell within the interquartile range of the model predictions. Eleven of the remaining days at which the measured data fell outside the interquartile range had measured values at or below the LOQ and were therefore set to 0.5 ug/kg for purposes of this analysis. Only five days with measurements greater than the LOQ fell outside of the interquartile range. All measurements were within the bounds of the prediction interval. In year 2, four of thirty-six measured values fell within the interquartile range. But twenty-two of the days exhibited values less than or equal to the LOQ. The remaining measured values were less than 5 ug/kg.

Only three measured values for pesticide in pore water were greater than the LOQ (set to ½ the LOQ or 0.05 ug/L for purposes of the analysis) in year 1, and the largest of these three values is 0.48 ug/L. In year 2, twelve of the twenty-eight measured values were less than or equal to the LOQ. The model underpredicted the measured values in 26 of the 28 possible cases. Of the sixteen measured values greater than ½ the LOQ, the largest value was 1.16 ug/L, the remainder of the measured values were below 0.38 ug/L. Importantly, these measured concentrations are very small and border on environmental relevance.

For bromide in pore water in both years 1 and 2, the measured values did not fall within the interquartile range of model outcome distributions. Eight measured values were equivalent to ½ the LOQ (0.05 mg/L) and the remaining 49 measured values ranged from 0.10 to 113.30 mg/L. Model distribution outcomes underpredicted the measured values 40 of the 54 cases and overpredicted the remaining 12 cases. Measurements and model distribution outcomes while typically not overlapping were increasingly more correlative with depth and time. Importantly, the estimated spatial and temporal profile or pattern of pore water bromide movement through the soil core was highly correlated to the measured data. Several conclusions can be drawn from the data 1) in this instance the model can be considered inaccurate with regard to estimating the magnitude of the bromide pore water concentration on a daily basis and 2) the model can be considered accurate in estimating the spatial and temporal movement of the tracer. The discrepancy in the magnitude of the estimated and measured pore water bromide concentrations is likely due to the inability to precisely simulate bromide uptake by plant material, the sampling of soil pore water via suction lysimeters and its associated uncertainty and discrepancies related to estimating evapotranspiration.

Leaching: NC4L

Box-and-whisker plots are presented for leaching variables pesticide mass in soil (Figure A8-12), pesticide in pore water (Figure A8-13), and bromide in pore water (Figure A8-14). Percent exceedence calculations are presented in Tables A8-11 through A8-15.

In year 1 the predictive pattern of the model for large measured values of pesticide mass in soil ($\geq$ 150 ug/kg) was inconsistent with model outcome distributions both greater than or less than measured data. For smaller measured values ($\leq$ 50 ug/kg) the model outcome distributions tended to underpredict the measured data. As the depth increases and the measured concentrations decrease and the model does indeed predict small concentrations. In year 2, a similar pattern held with the model generally underpredicting small values. Again, as the depth of the soil profile increased and the measured concentrations decreased the model predicted very small concentrations. Beginning at the 45 to 60 cm soil core segment any discrepancies between model estimates and measured soil core pesticide concentrations were environmentally irrelevant.

Of the year 1 pesticide in pore water values greater than 10 ug/L, one fell within the interquartile range of the model predictions, and two more fell within the model prediction bounds. The model overpredicted one value at or below the LOQ. Of those concentrations greater than 0 and less than 10 ug/L, seven of the eight measured values were overpredicted by the model. No measured values were greater than 10 ug/L in year 2. The model underpredicted sixteen of the seventeen available data points that were however, small in magnitude.

Bromide soil pore water prediction distributions and measured data generally show a similar pattern with depth and time. Of the eighteen available measured data points, one fell within the interquartile range of the model distribution outcomes. The model underpredicted eight values. However, the magnitude of the differences between the measured data and estimate distributions were generally minimal.

Discussion

These results serve to demonstrate the feasibility and utility of evaluating the effects of model input uncertainty on PRZM3.12 outcomes. In general, when model input uncertainty was accounted for, the correlation of model outcome distributions and measured data was reasonably to exceptionally well correlated. This conclusion can be drawn in spite of the fact that the uncertainty bounding the measured values was not factored into the analysis. Pennell et al. (1990) conclude that the ability to validate model predictions of concentration distributions may ultimately be limited by the inability to account for the uncertainty in measured data from within the field. Given the expected uncertainty in the measured data the degree of prediction error and measurement error would make it increasing difficult to detect differences.

The current state of the science with regard to exposure analysis is such that evaluation of model predictive accuracy is often assessed via the factor-of-f approach (Parrish and Smith, 1990; Parrish et al., 1992; and van den Bosch and Boesten, 1998). Comparisons of model estimates versus measured values are often considered successful within 2-, 5- and 10-fold differences. The Monte Carlo driven output distribution approach extends the factor-of-f approach discussed within the literature because it adds an empirical aspect to the analysis. Rather than set an arbitrary level for accuracy, i.e., a factor of 5, this approach allows the nature of the measured data serving as input to set the bounds that define the precision of the model. Measured values falling within the interquartile range of an outcome distribution lead to the conclusion that the model is reasonably predictive. Given the state of the science of exposure analysis, even when measured values fall within the outcome distribution bounds the model should be considered predictive. It is important to note however that the scale of the measurement influences the degree of required accuracy. Based on the current analysis, it has been shown that for small concentrations, e.g., less than 5 ug/L of pesticide or pesticide concentrations approximating the LOQ, the criteria for accuracy need not be as rigorous. Differences in model outcome distributions and measured data in instances where the magnitude of the scale of the measured data is small or approaches the LOQ, become less critical. Typically the magnitude of those differences are beyond the desired level of model accuracy and environmental relevance.

An important aspect of the current approach that should be emphasized is that the nature of the input distributions define the output distributions. Subjective and incorrect assumptions about the nature of the input distributions while allowing for the generation of seemingly accurate output distributions can provide spurious results. In the process outlined within this discussion, the nature of the input parameter distributions were carefully explored as deeply as the data would allow. In those instances where there was considerable uncertainty about the input parameter distribution, the conservative assumption was taken. Typically, a uniform distribution was assigned to those uncertain input parameter distributions where any one value within the bounds of the distribution had an equal probability of selection. One flaw in the current analysis is the depth of information about each of the available input parameters. Future work should focus on enriching the database from which these assumptions about distributions can be made.

Loague and Green (1991) and others note that statistical analyses using pair-wise correlation or hypothesis testing can suffer from potential serious flaws due to sample size deficiencies. Preliminary efforts for this study centered on pair-wise correlation and hypothesis testing statistical approaches for estimating model accuracy. Ultimately, the efforts refocused on the Monte Carlo approach because the classical statistical approach was hampered by small sample sizes and differences in phase timing that led to conclusions of reduced model accuracy.

Importantly, the Monte Carlo approach lends itself to the current trend in environmental risk analyses where stochastic predictions are favored over single point deterministic results. Clearly, under environmental conditions the magnitude of associated uncertainties makes the utility of a single deterministic model prediction debatable.

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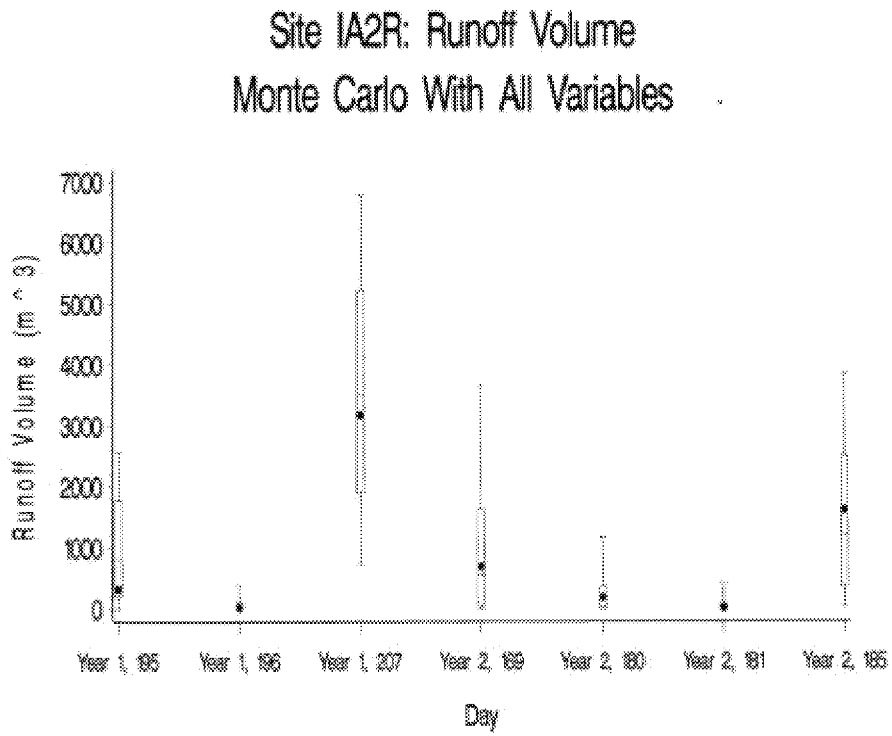
Figure A8-1. Results of Monte-Carlo simulations for IA2R.



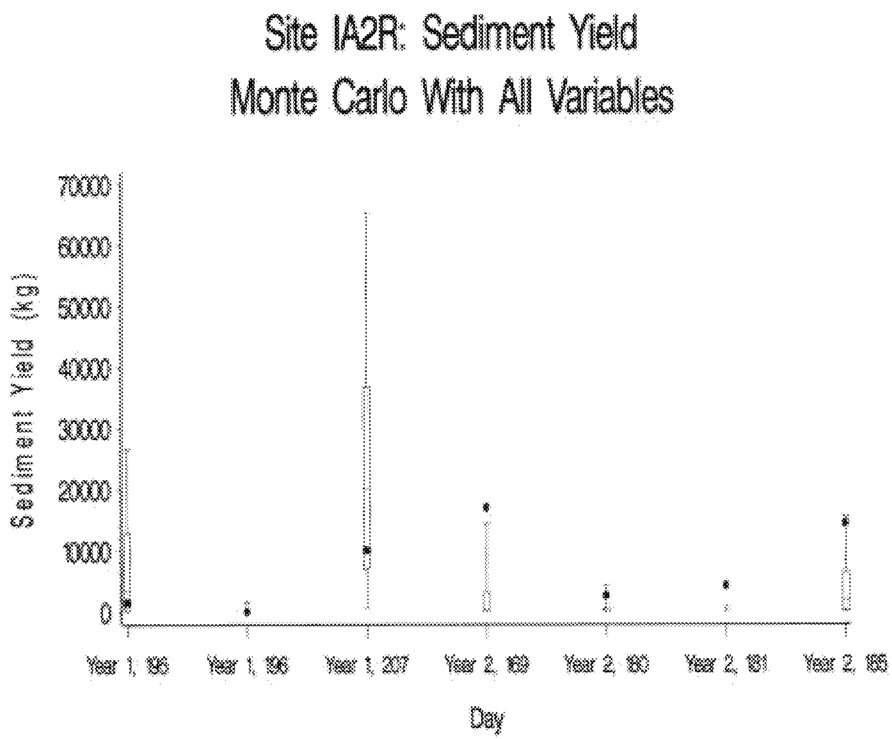
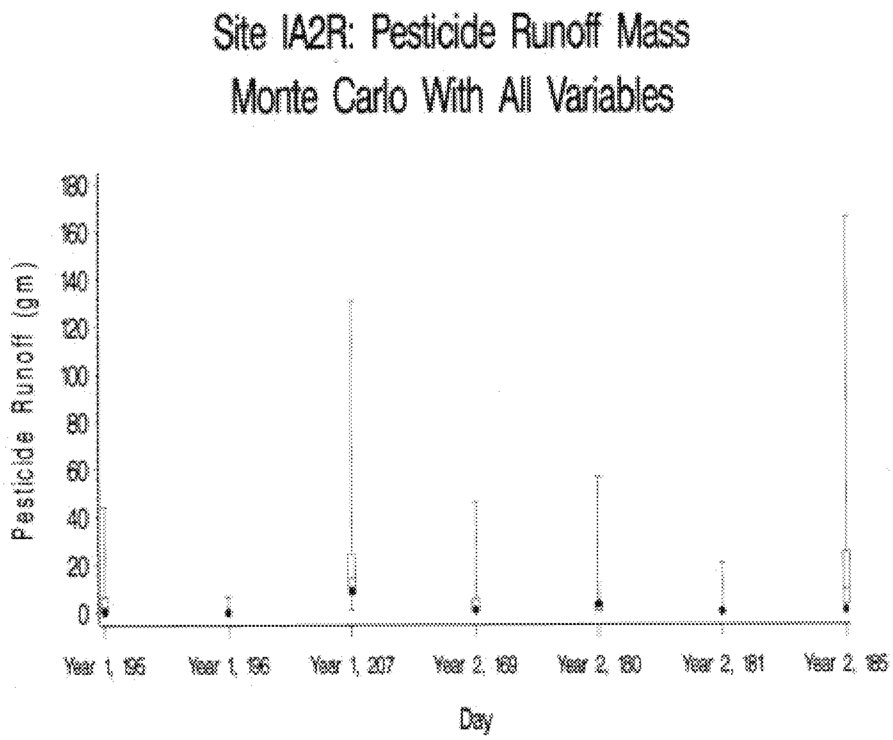


Figure A8-1 (continued). Results of Monte-Carlo simulations for IA2R.



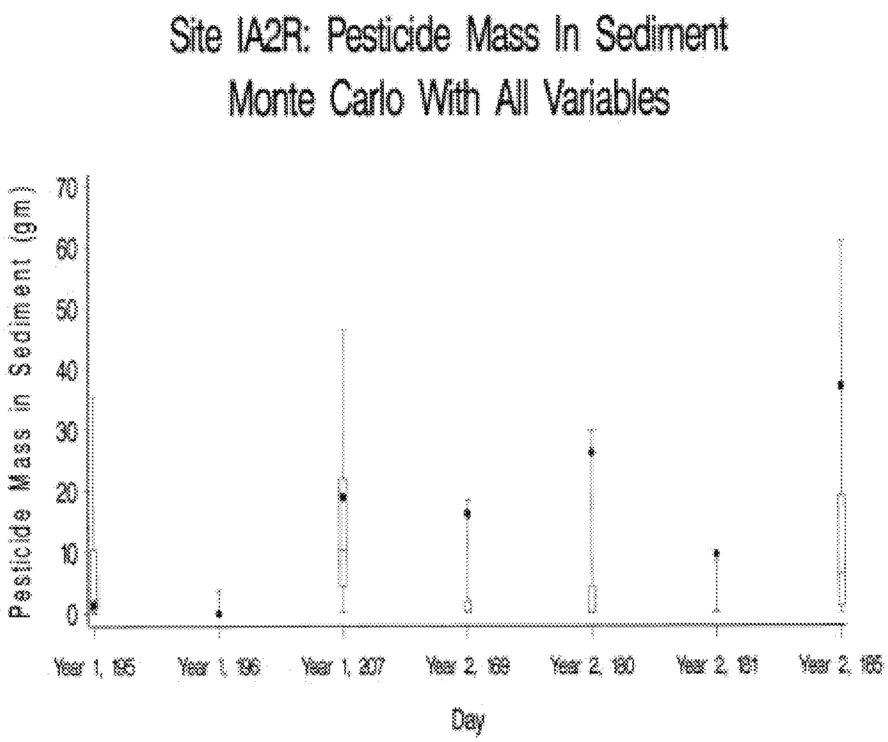


Figure A8-2. Results of Monte-Carlo simulations for GA1R.

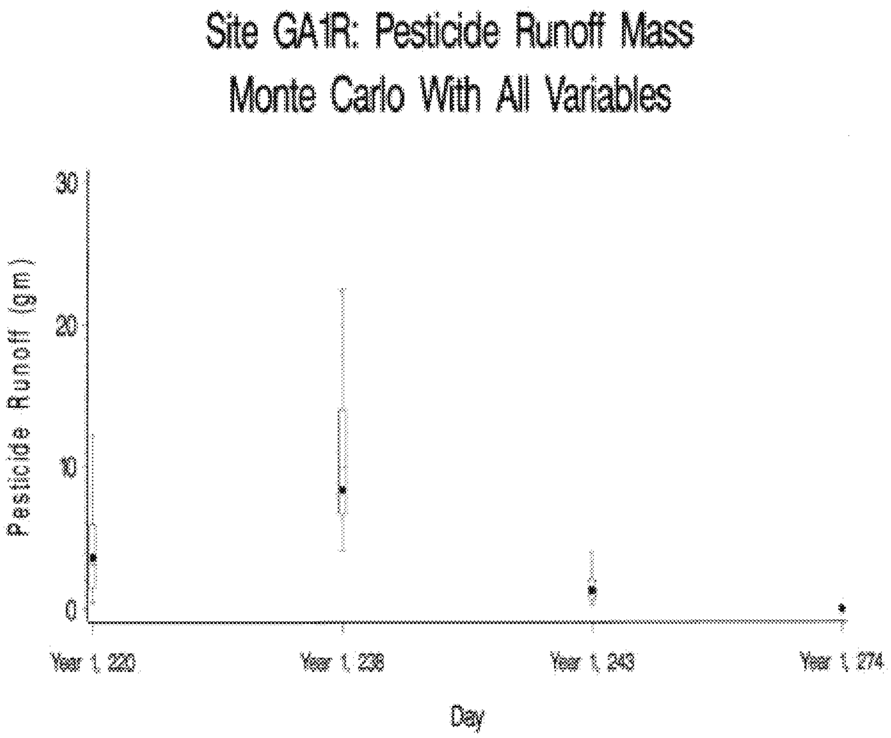
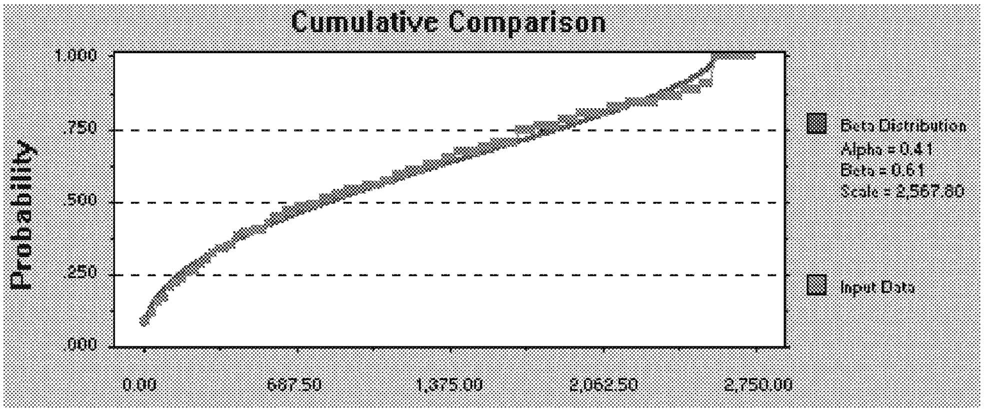
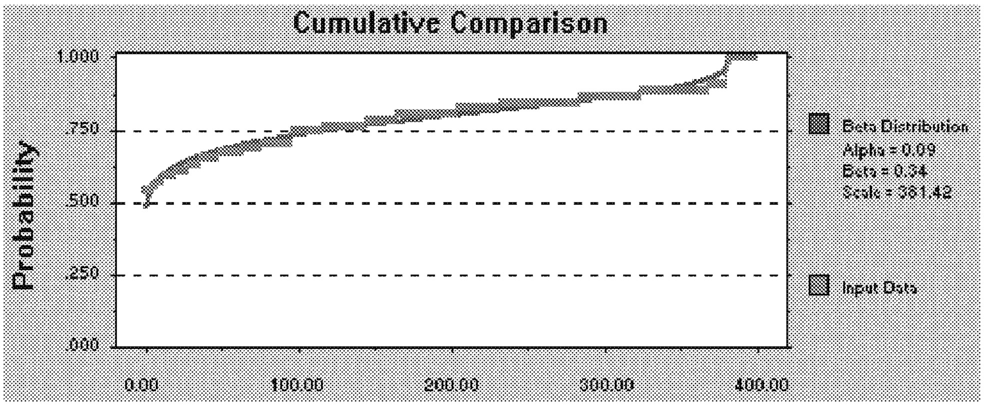


Figure A8-3. Output distributions from the PRZM Monte-Carlo procedures for site IA2R.

a. Runoff Volume (m^3): 1992, Day 195



b. Runoff Volume (m^3): 1992, Day 196



c. Runoff Volume (m^3): 1992, Day 207

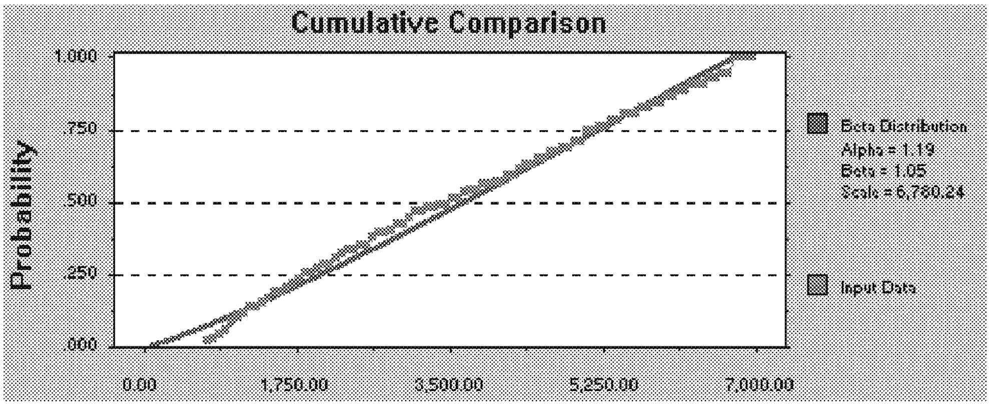
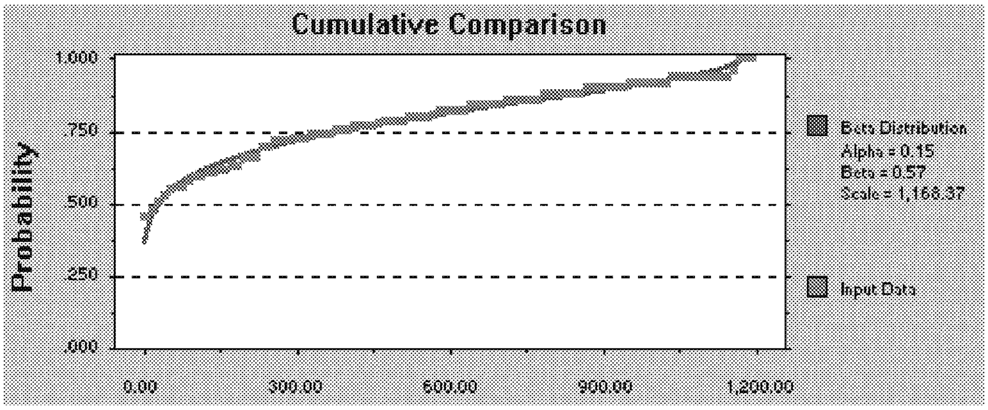
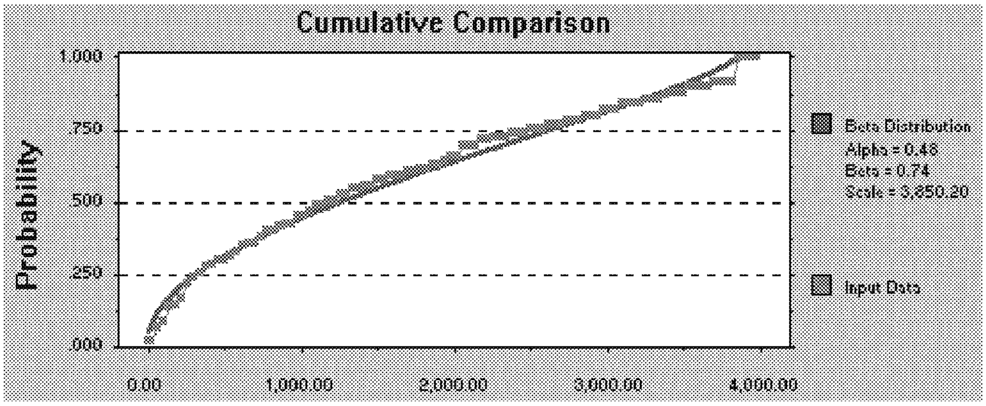


Figure A8-3 (continued). Output distributions from the PRZM Monte-Carlo procedures for site IA2R.

d. Runoff Volume (m^3): 1993, Day 169



e. Runoff Volume (m^3): 1993, Day 180



f. Runoff Volume (m^3): 1993, Day 185

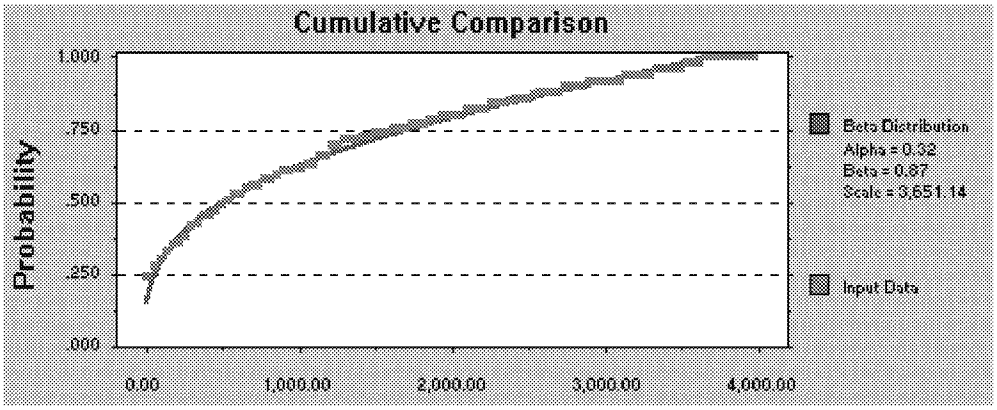
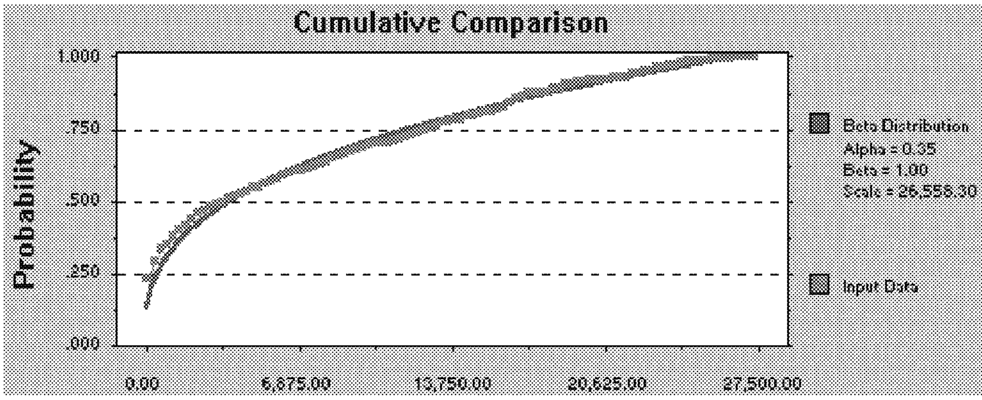
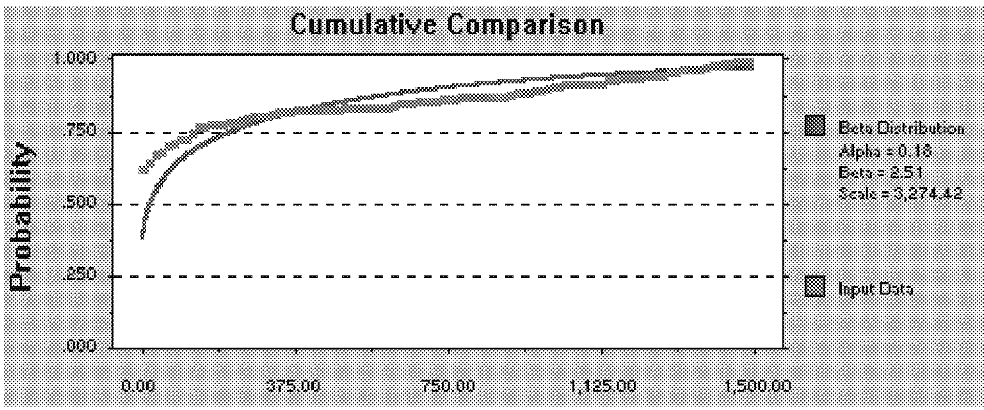


Figure A8-3 (continued). Output distributions from the PRZM Monte-Carlo procedures for site IA2R.

g. Sediment Yield (kg): 1992, Day 195



h. Sediment Yield (kg): 1992, Day 196



i. Pesticide Runoff Mass (g): 1992, Day 195

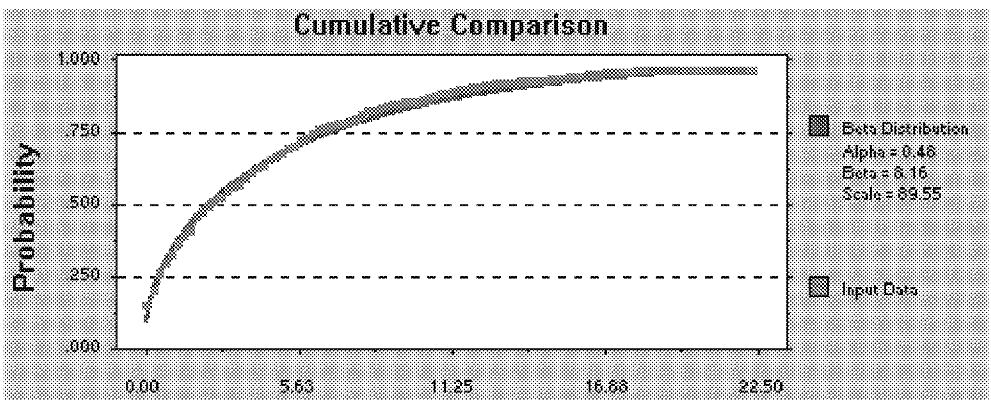
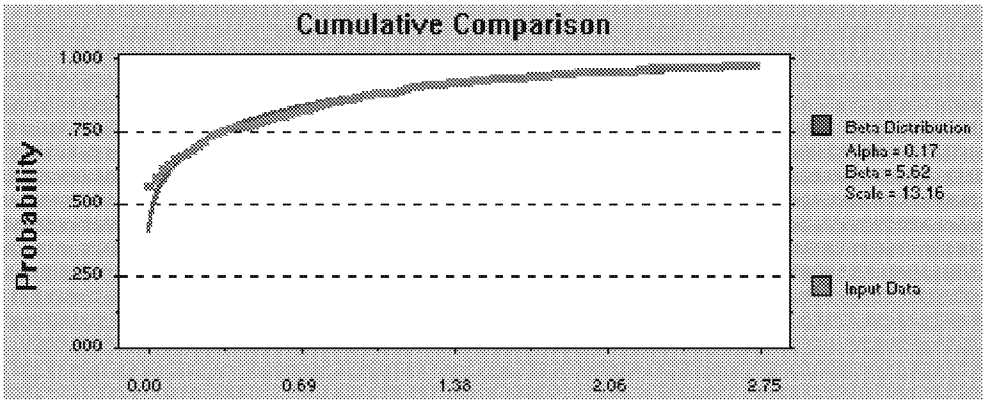
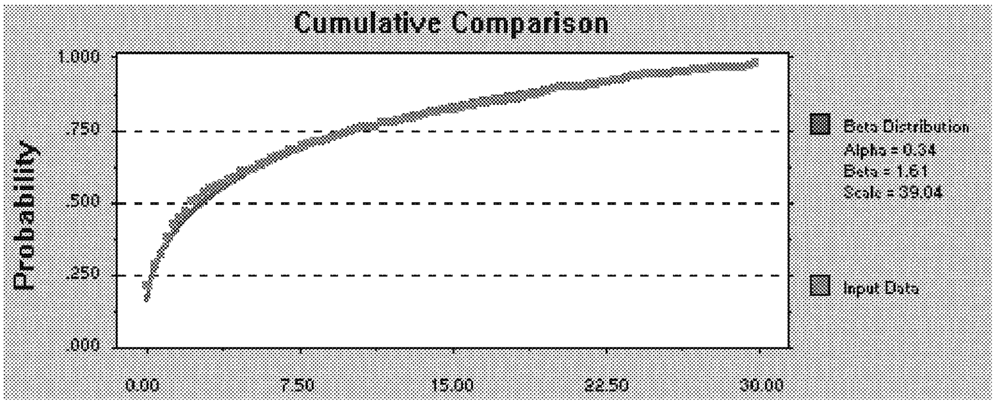


Figure A8-3 (continued). Output distributions from the PRZM Monte-Carlo procedures for site IA2R.

j. Pesticide Runoff Mass (g): 1992, Day 196



k. Pesticide Mass in Sediment (g): 1992, Day 195



l. Pesticide Mass in Sediment (g): 1992, Day 196

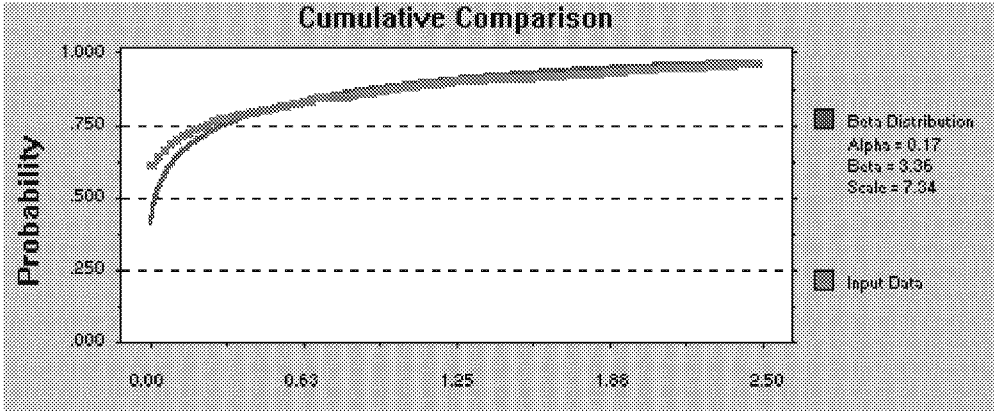
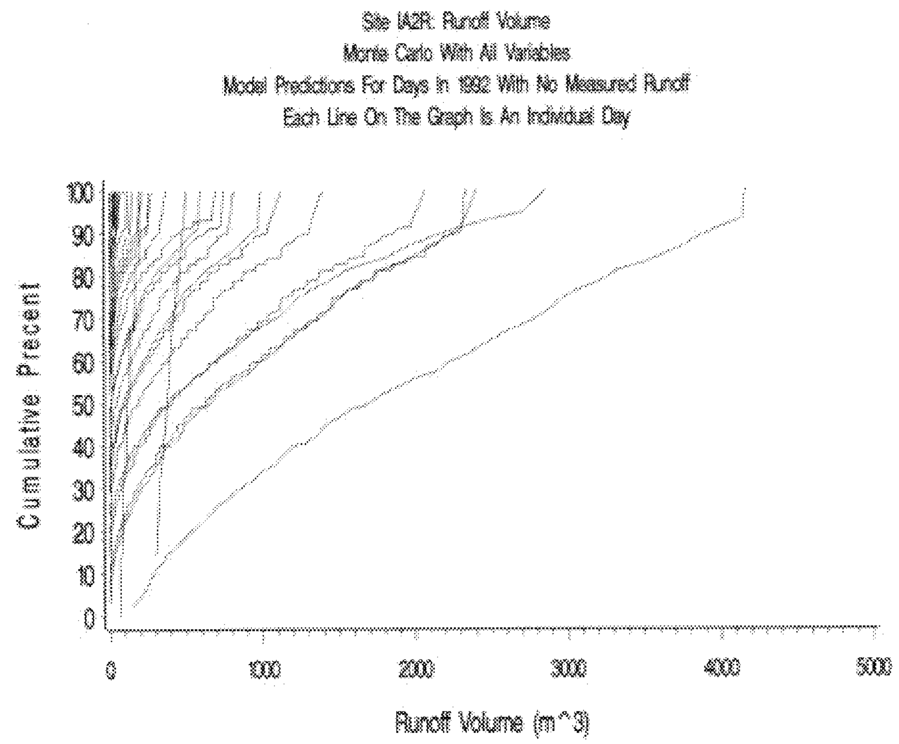


Figure A8-4. Runoff volume on days in 1992 and 1993 with no measured rainfall at site IA2R.



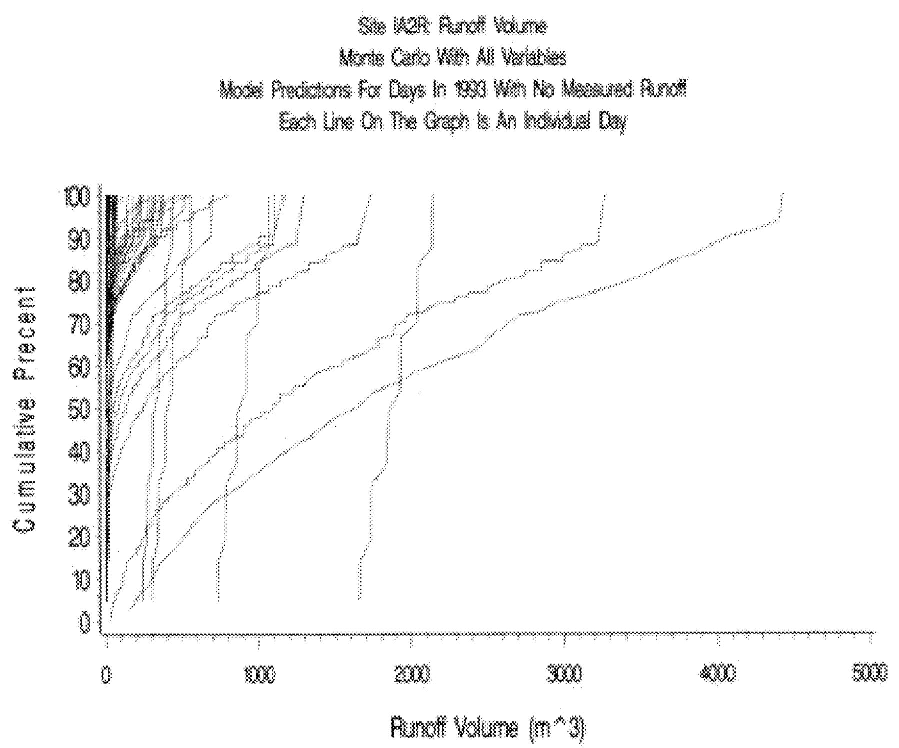
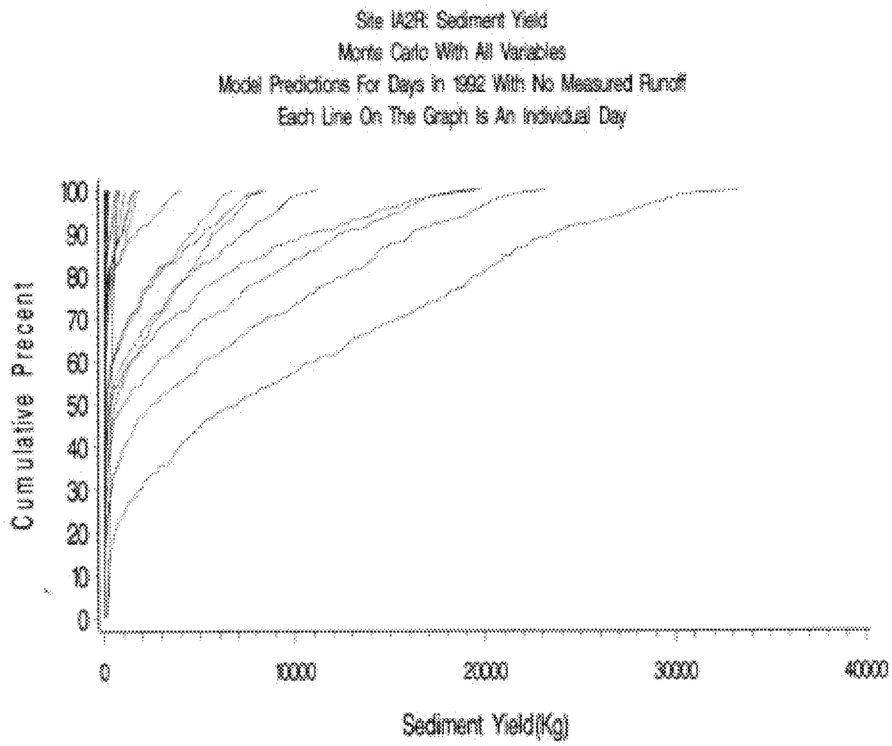


Figure A8-5. Sediment yield on days in 1992 and 1993 with no measured rainfall at site IA2R.



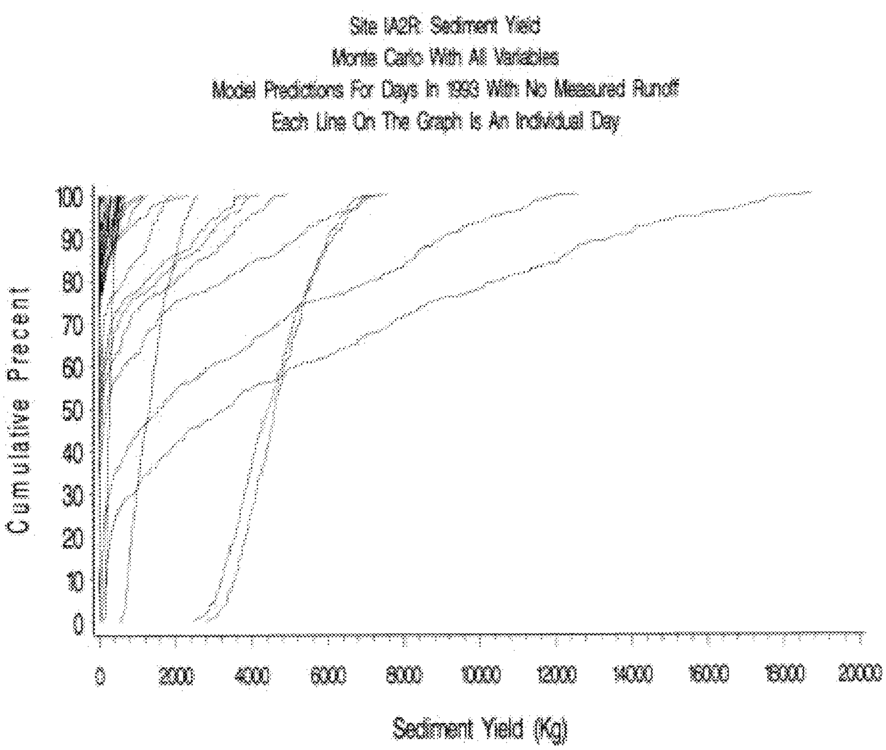
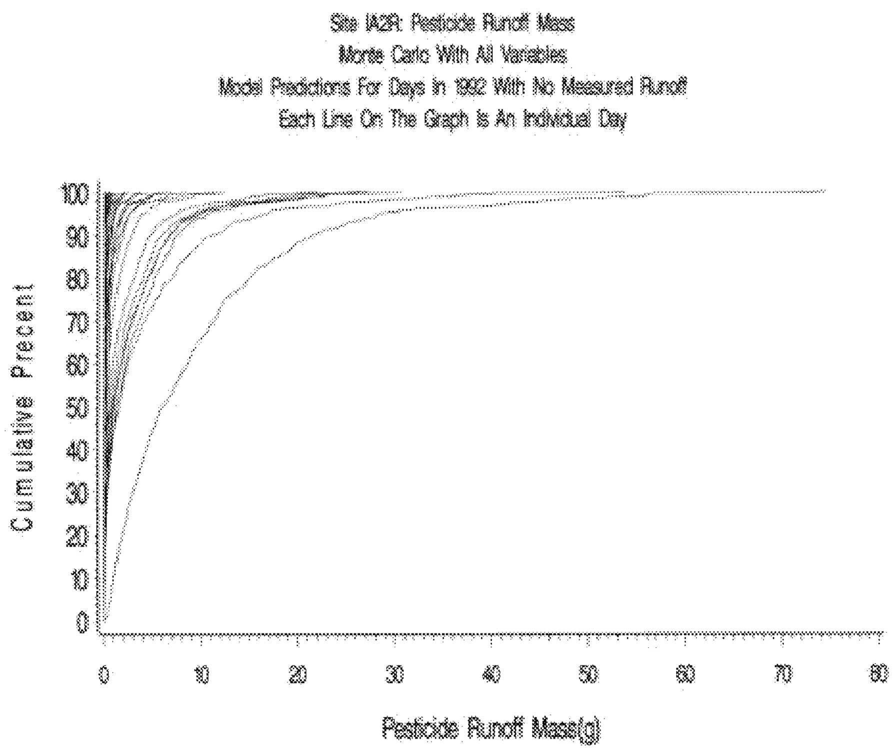


Figure A8-6. Pesticide runoff mass on days in 1992 and 1993 with no measured rainfall at site IA2R.



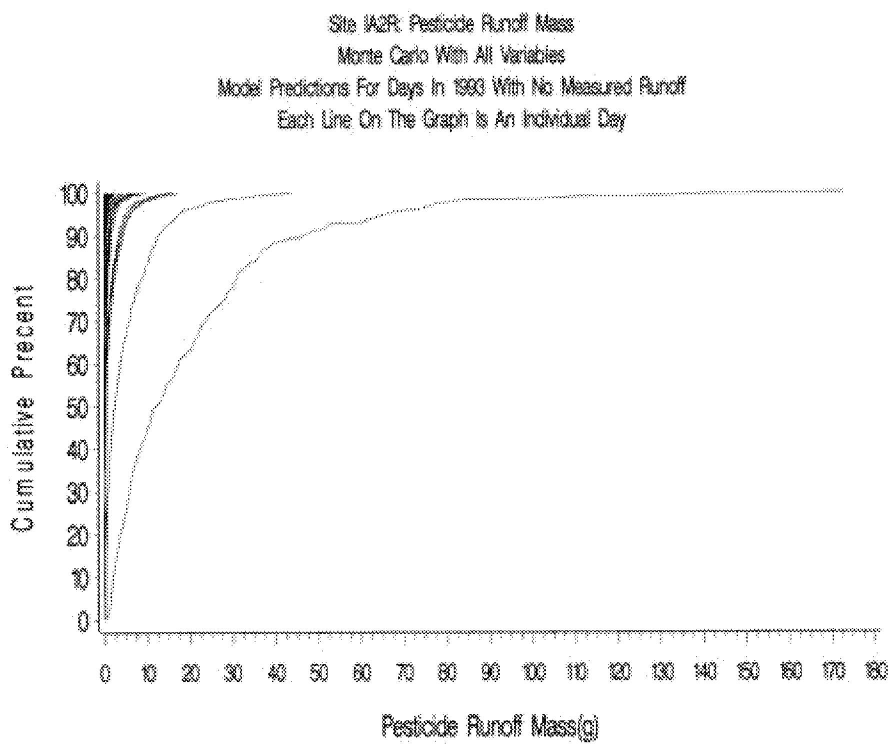
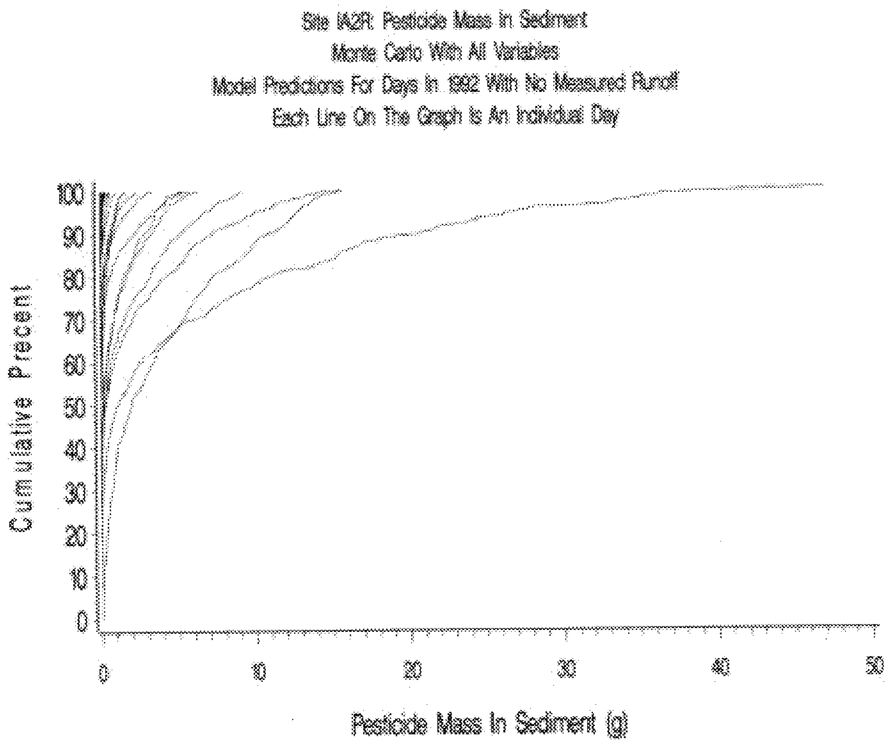


Figure A8-7. Pesticide mass in sediment on days in 1992 and 1993 with no measured rainfall at site IA2R.



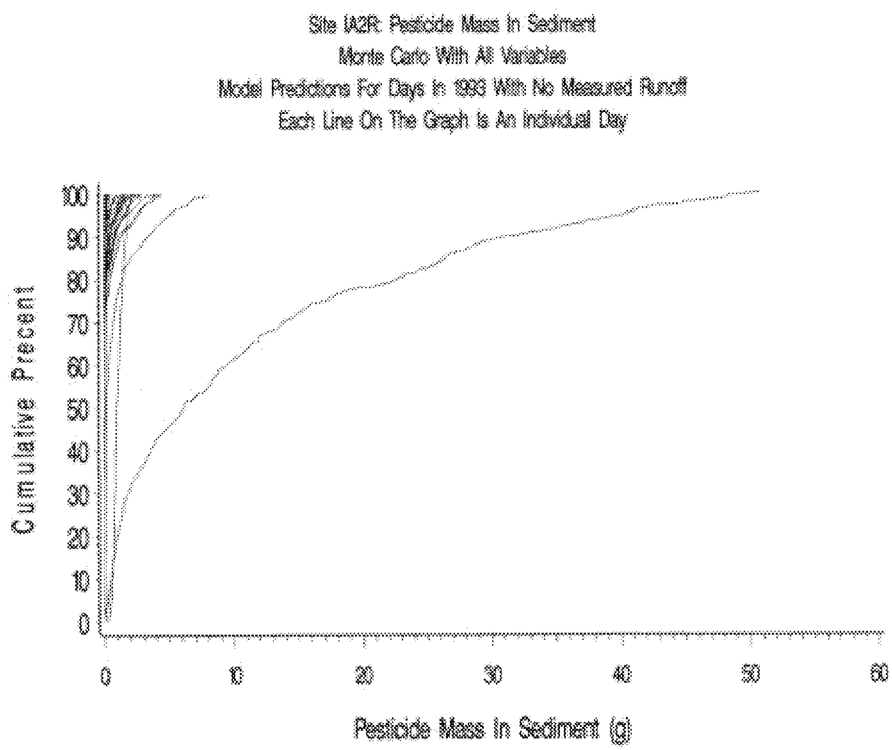


Figure A8-8. Pesticide runoff mass on days with no measured rainfall at site GA1R.

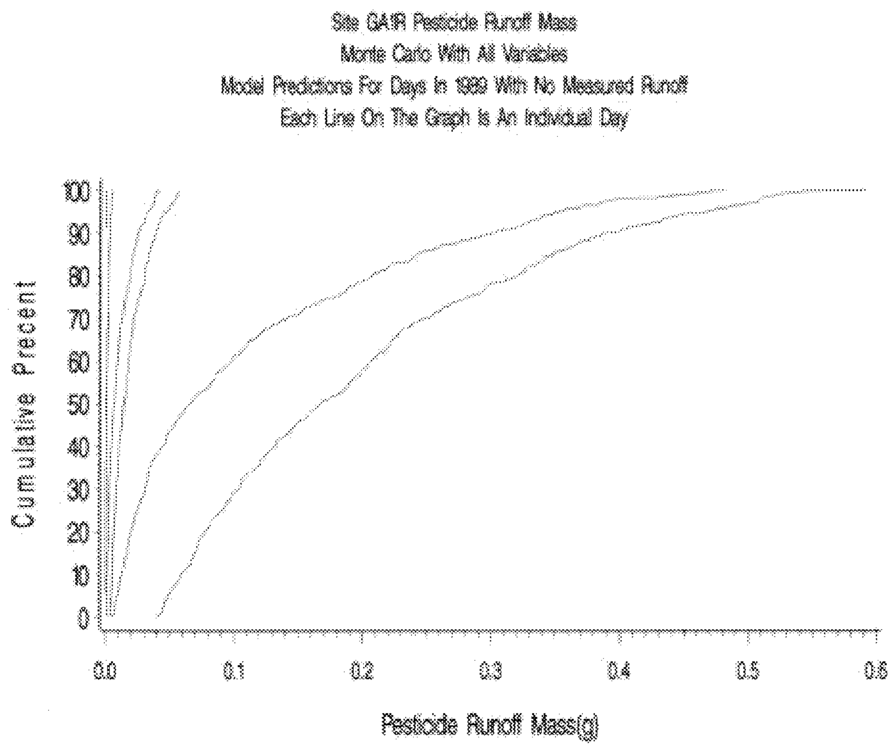
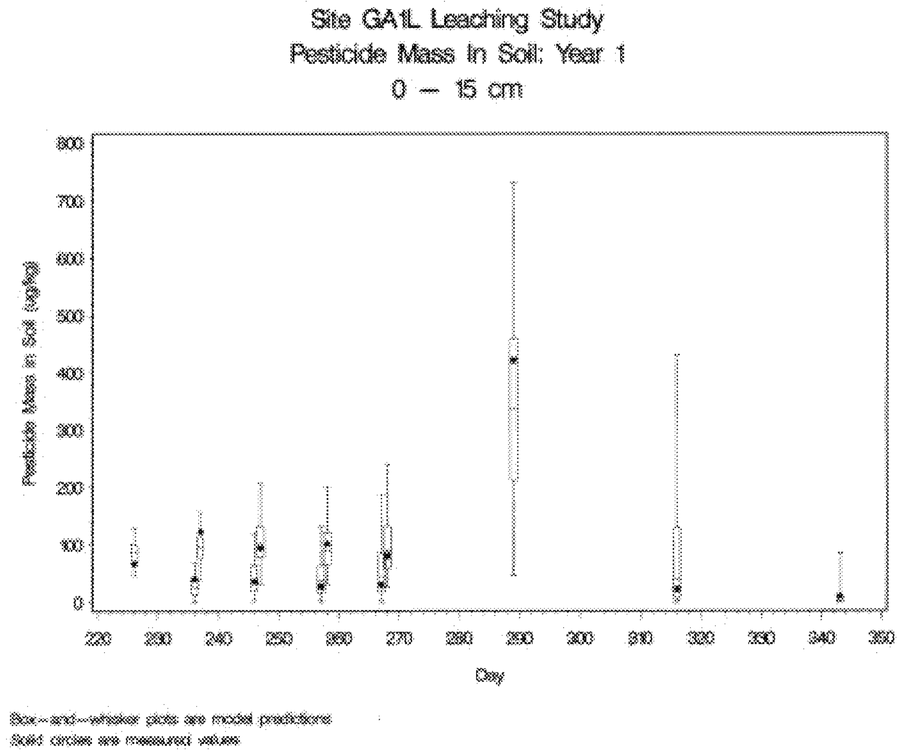


Figure A8-9. Results of Monte-Carlo simulations for pesticide mass in soil at site GA1L.



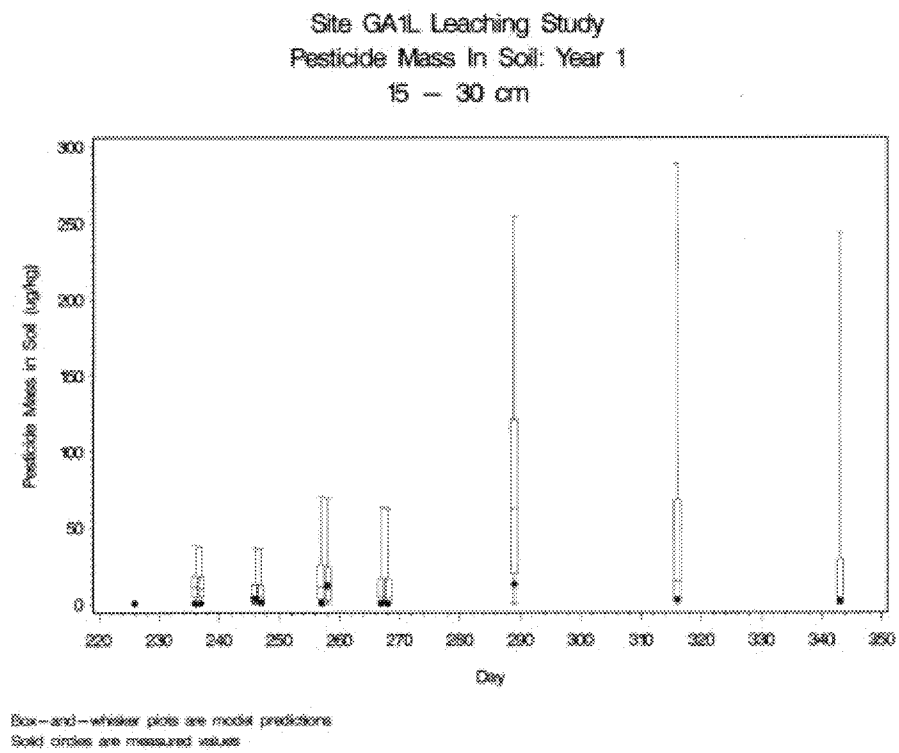
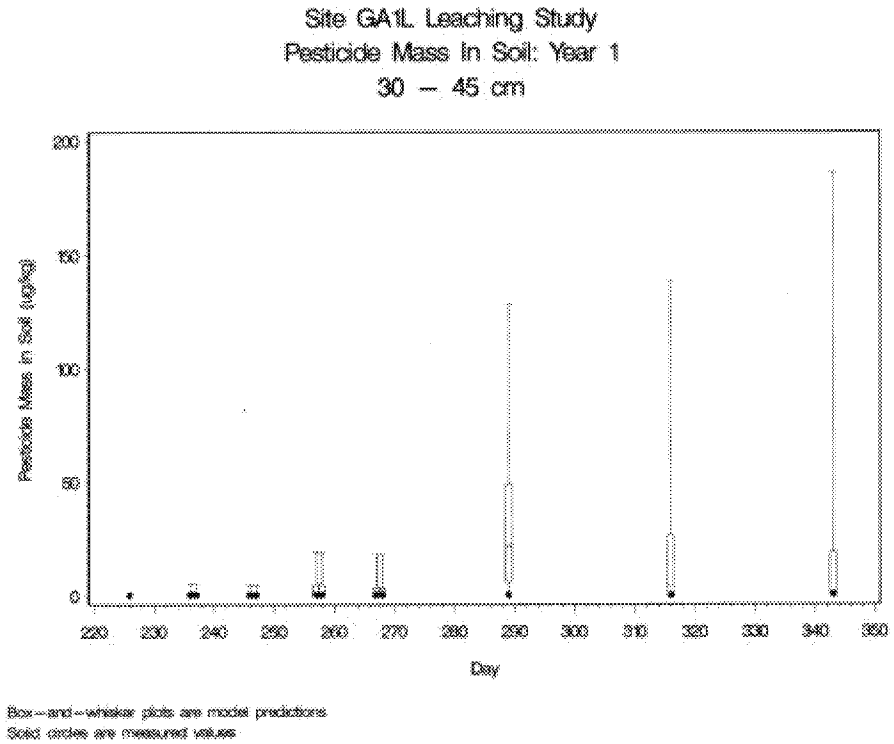


Figure A8-9 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site GA1L.



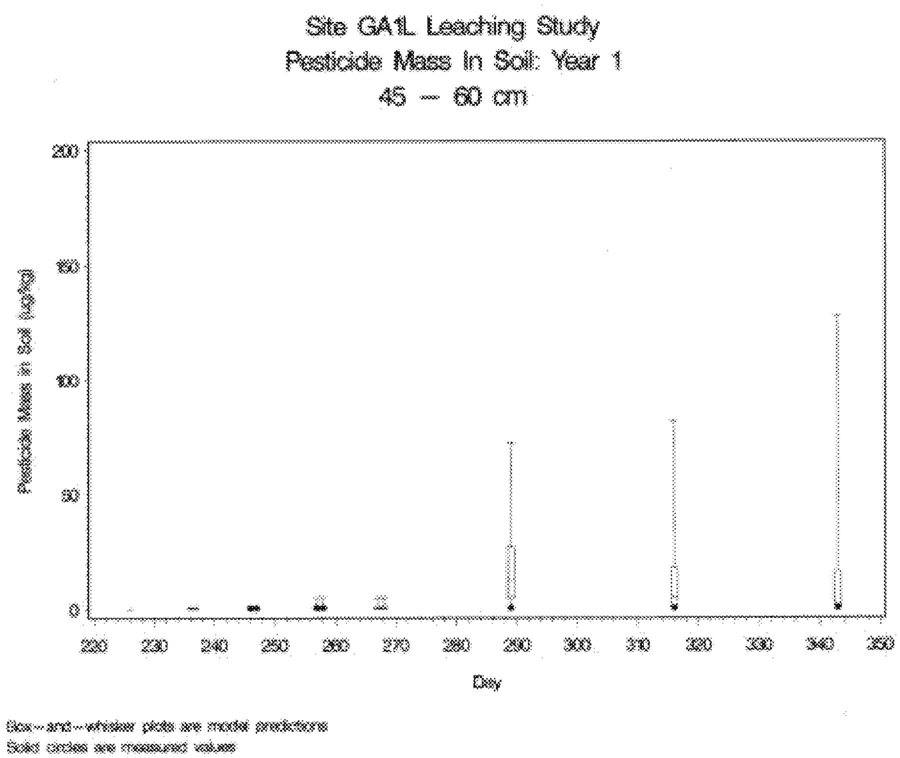
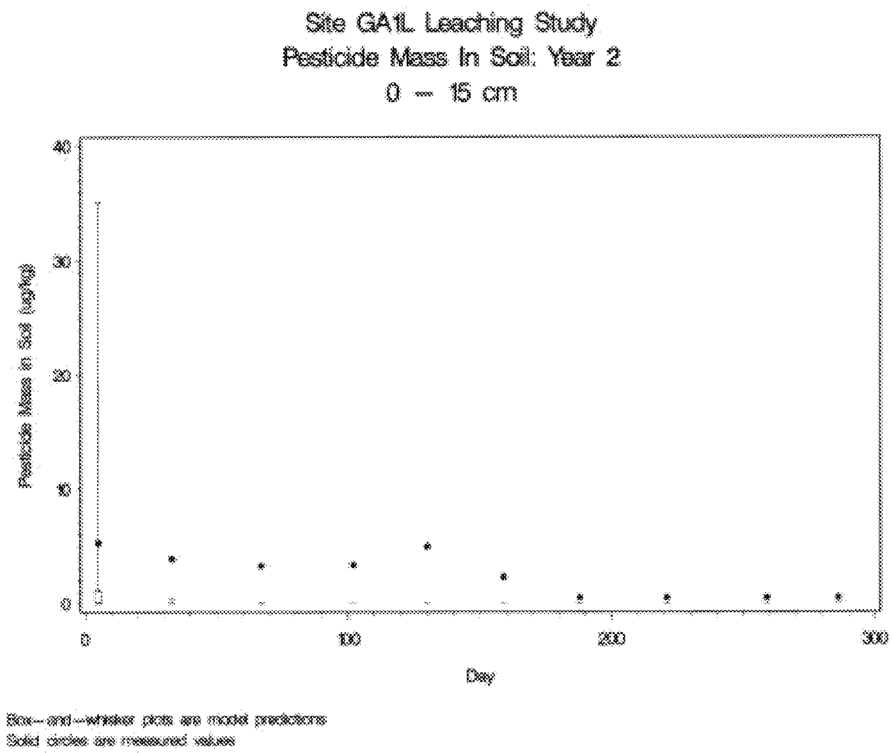


Figure A8-9 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site GA1L.



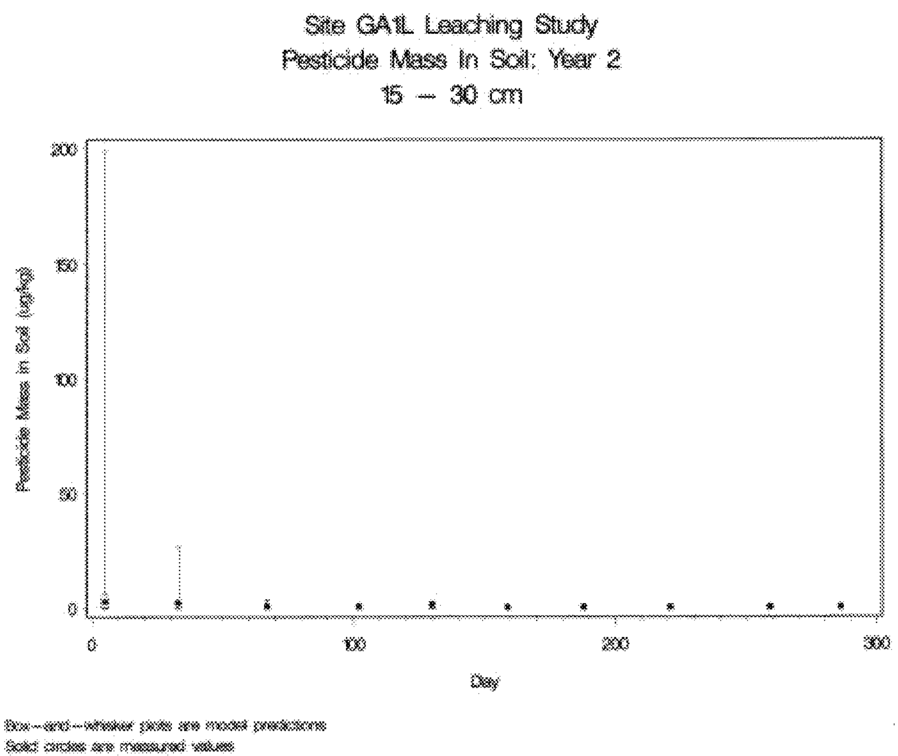
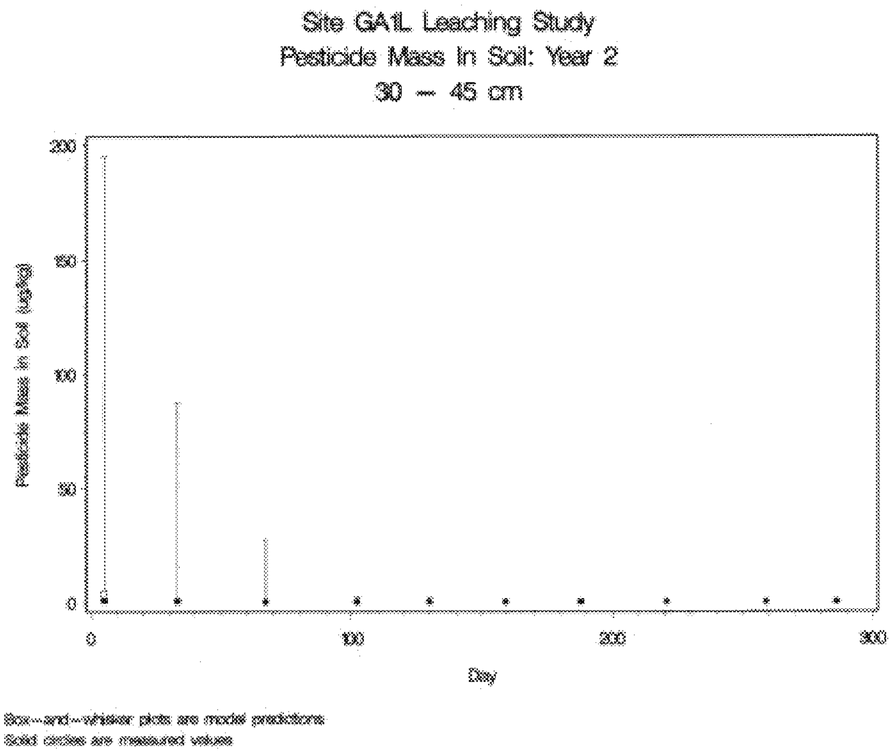


Figure A8-9 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site GA1L.



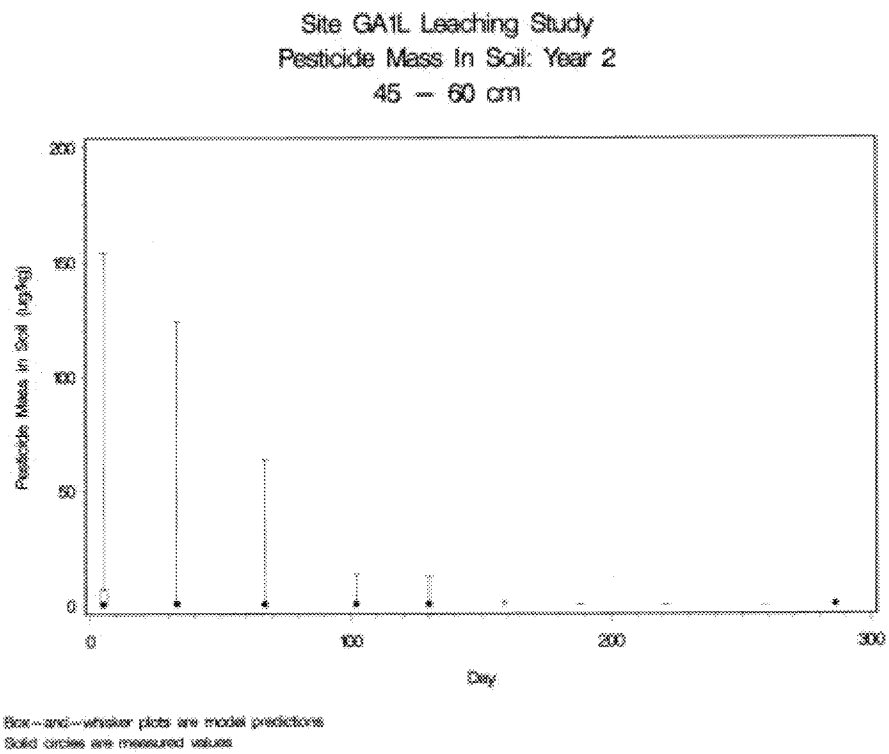
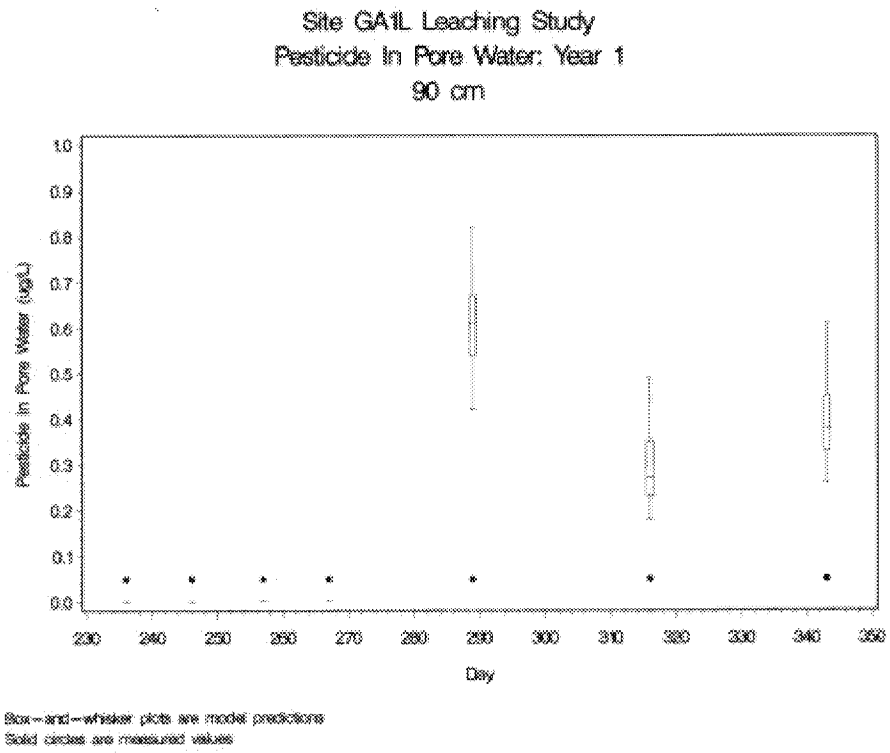


Figure A8-10. Results of Monte-Carlo simulations for pesticide in pore water at site GA1L.



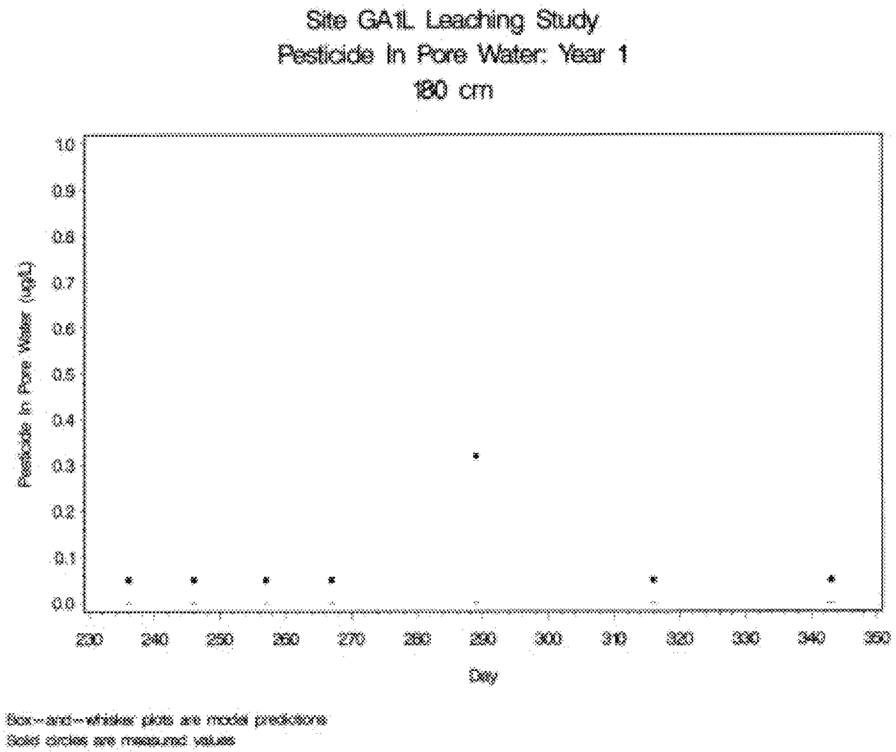
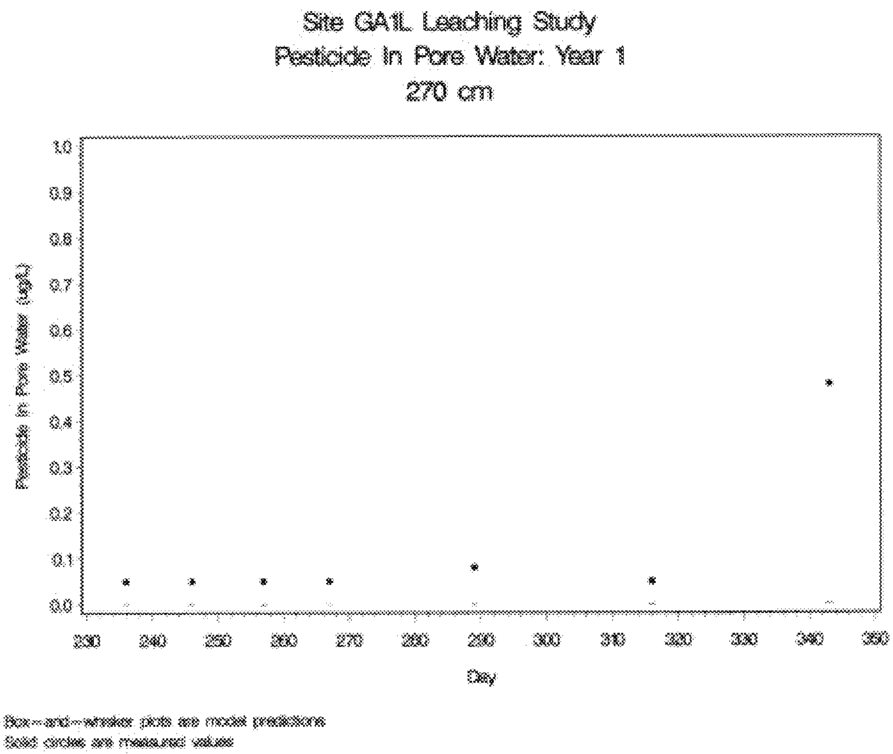


Figure A8-10 (continued). Results of Monte-Carlo simulations for pesticide in pore water at site GA1L.



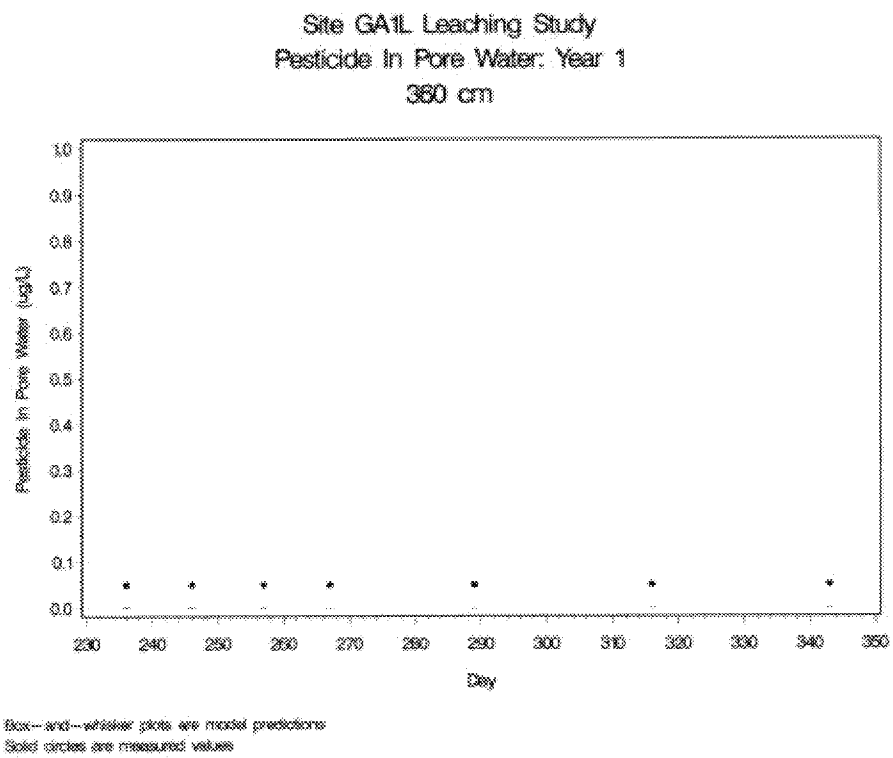
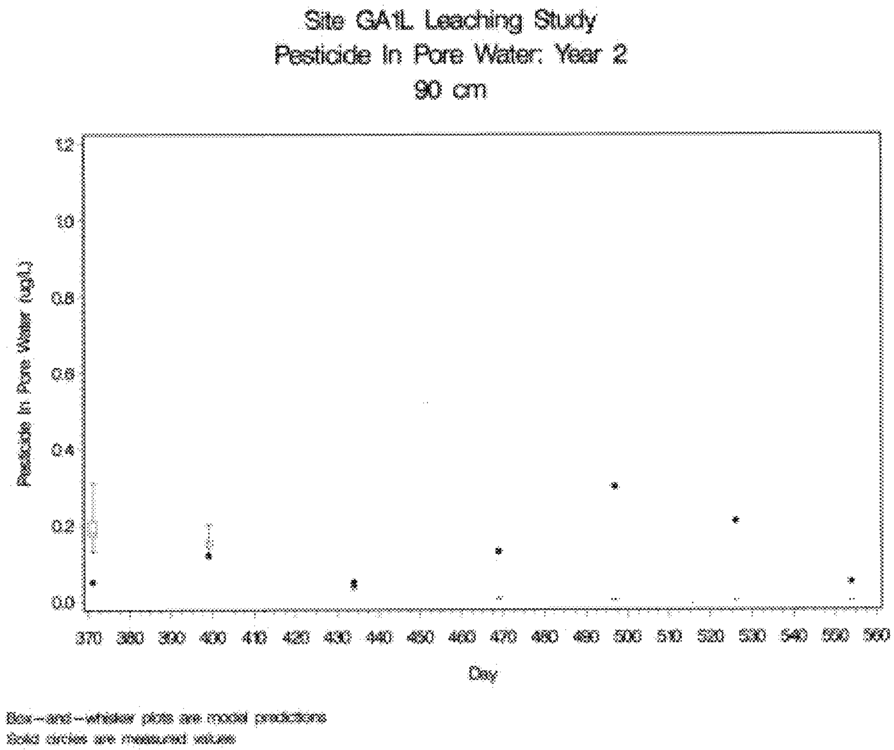


Figure A8-10 (continued). Results of Monte-Carlo simulations for pesticide in pore water at site GA1L.



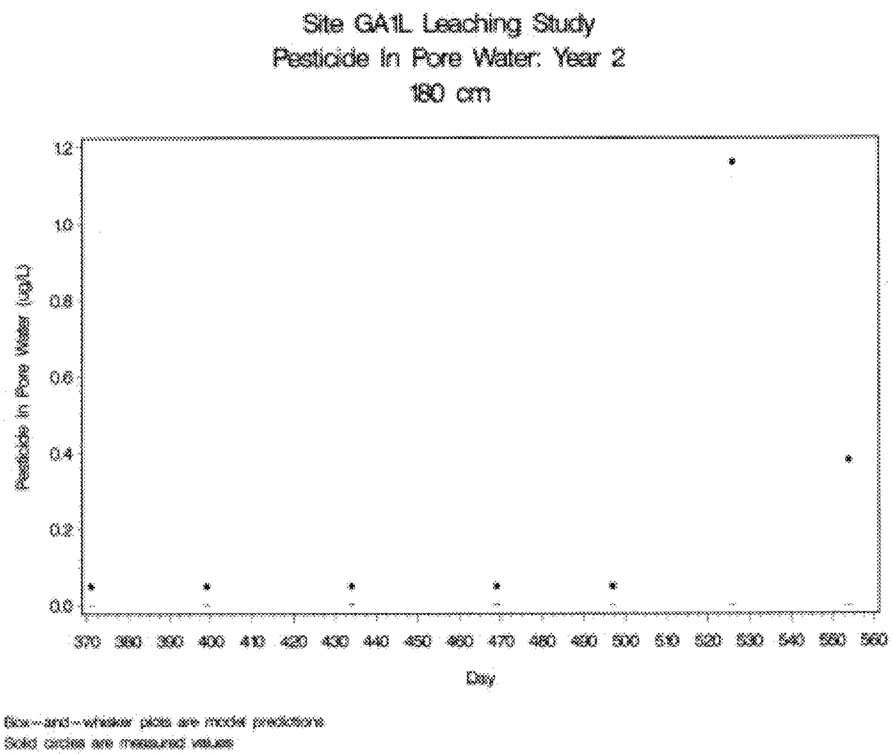
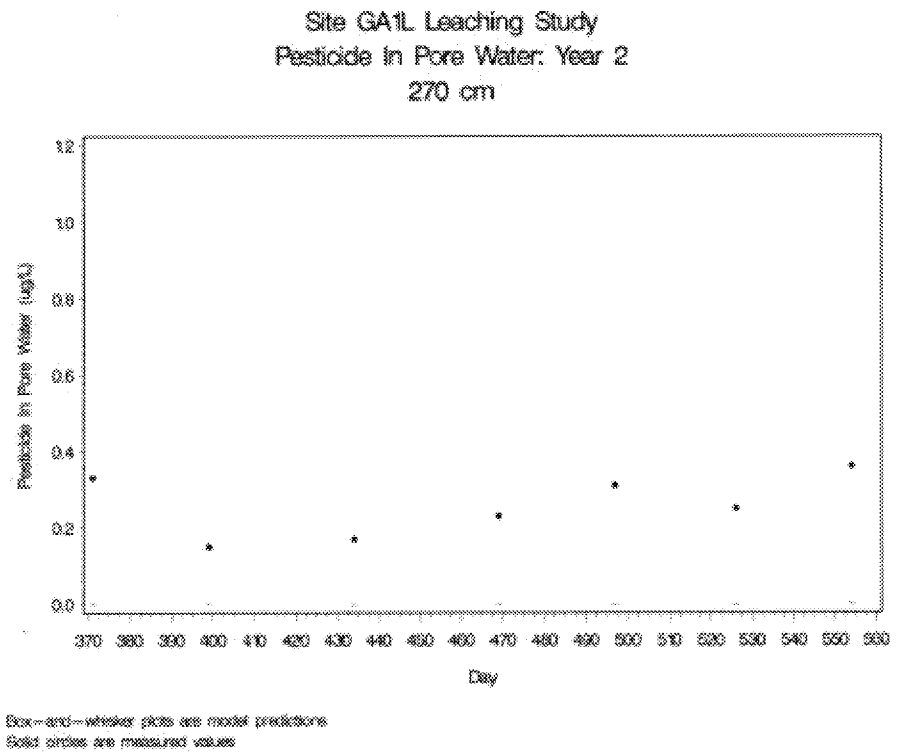


Figure A8-10 (continued). Results of Monte-Carlo simulations for pesticide in pore water at site GA1L.



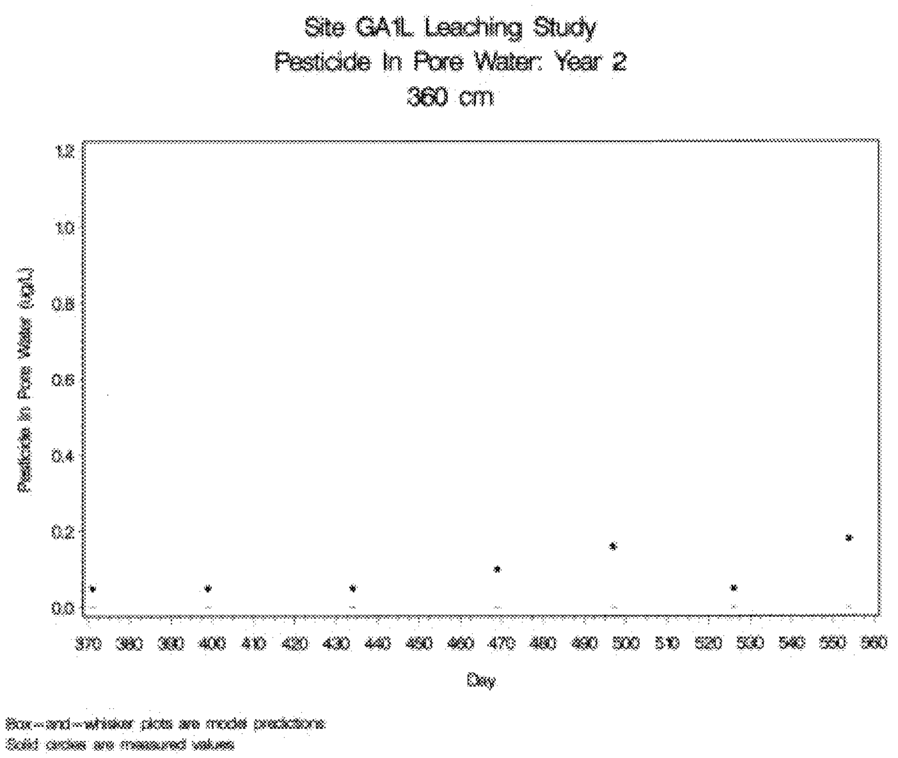
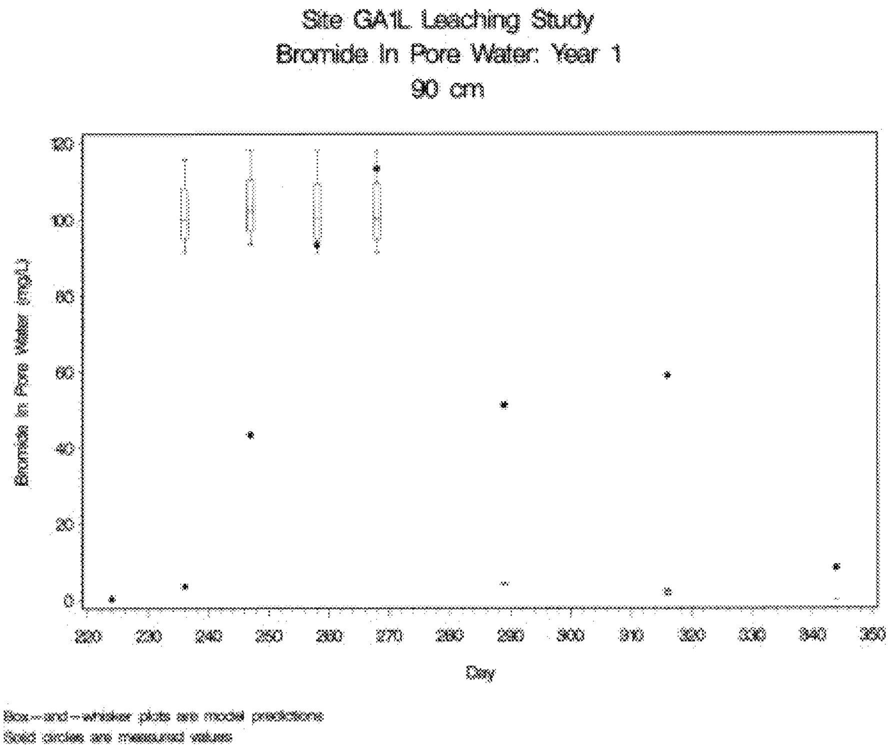


Figure A8-11. Results of Monte-Carlo simulations for bromide in pore water at site GA1L.



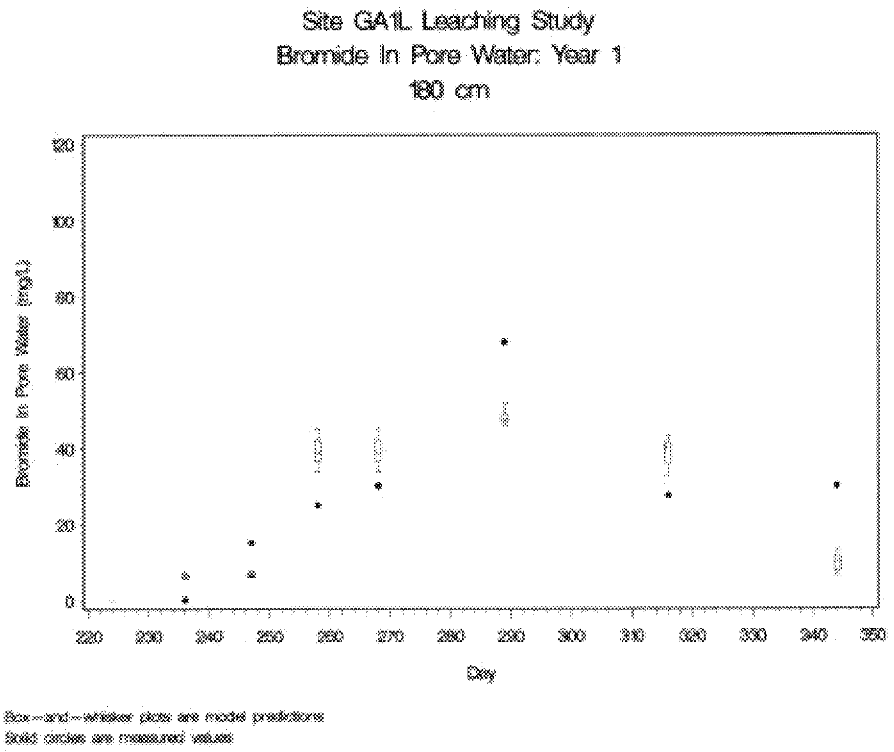
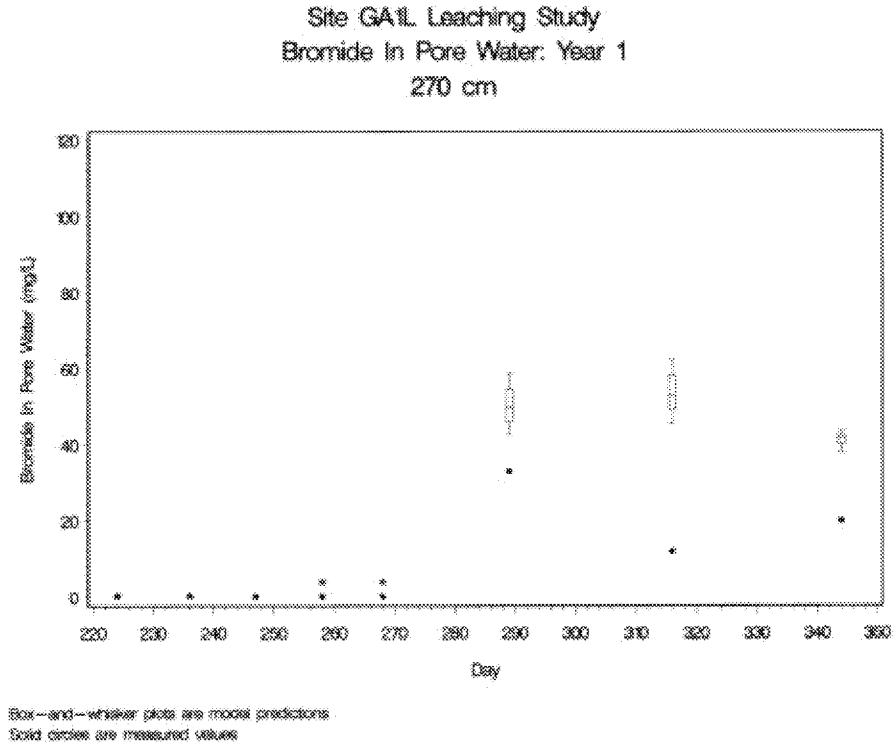


Figure A8-11 (continued). Results of Monte-Carlo simulations for bromide in pore water at site GA1L.



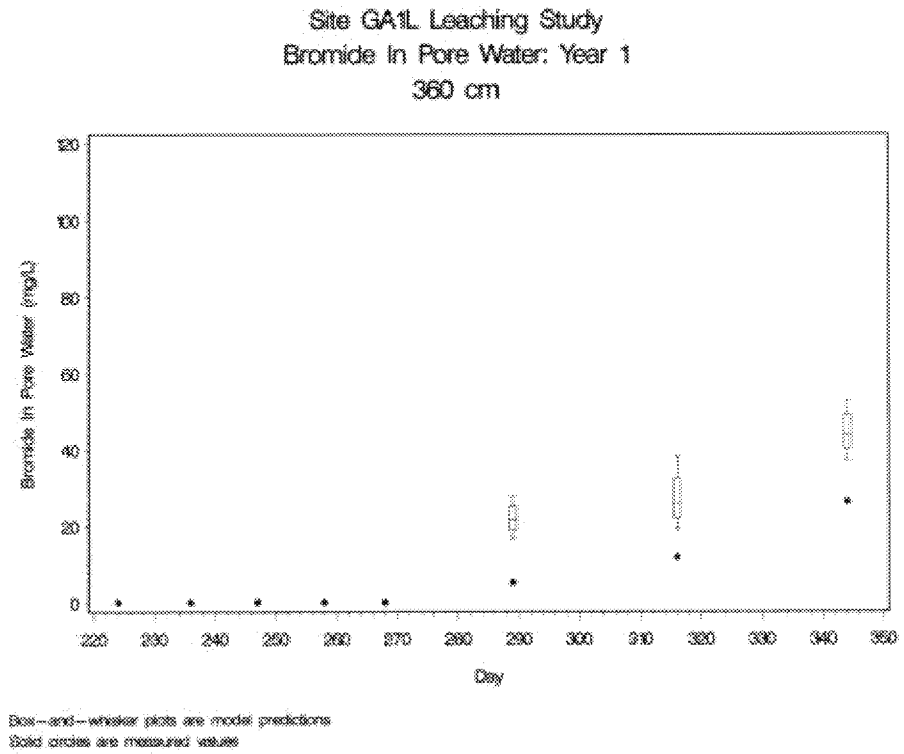
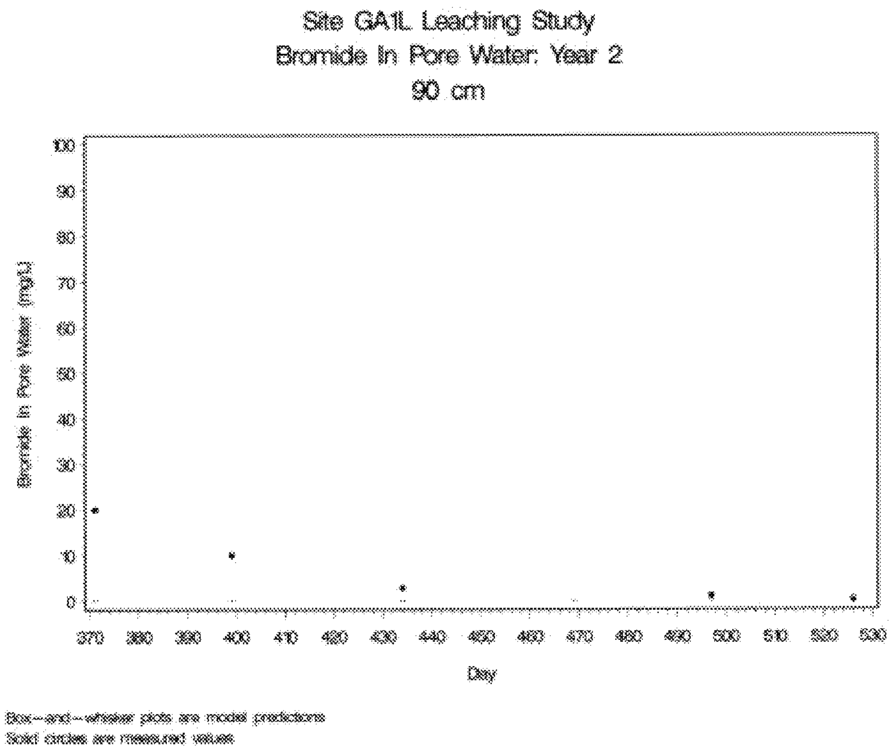


Figure A8-11 (continued). Results of Monte-Carlo simulations for bromide in pore water at site GA1L.



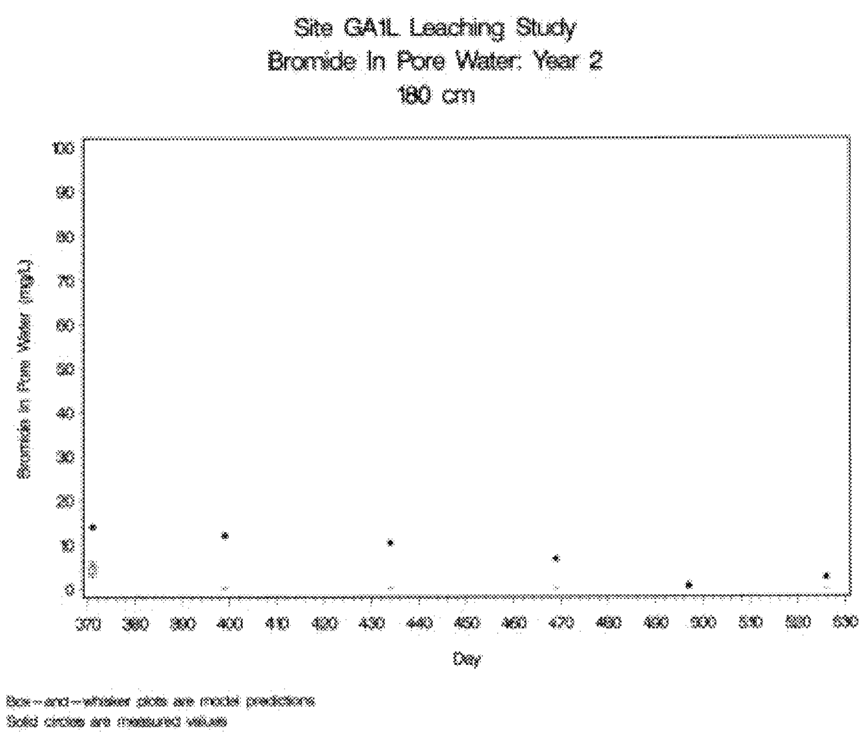
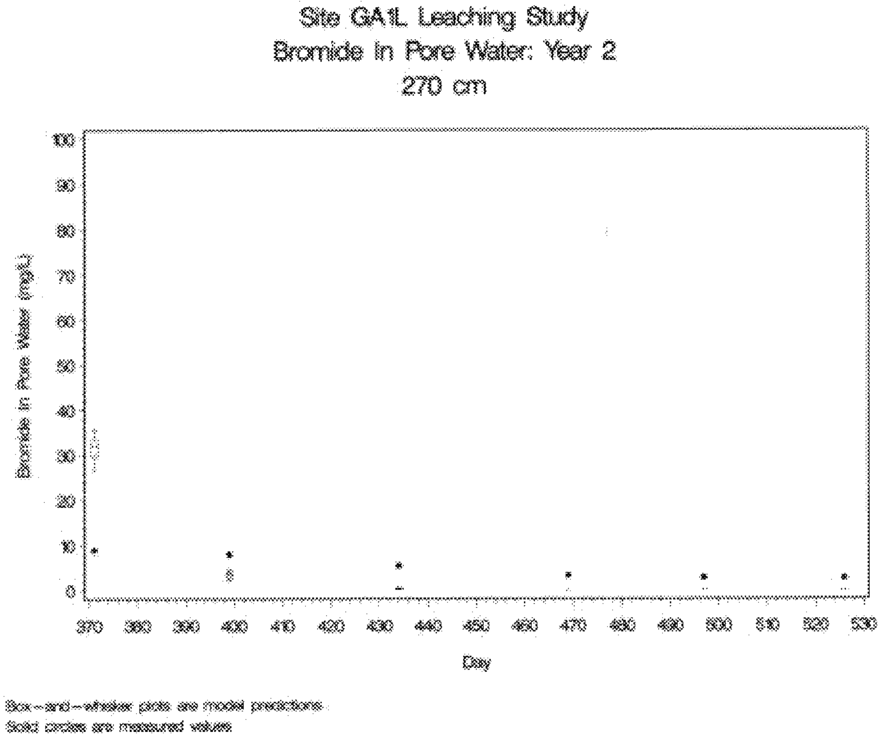


Figure A8-11 (continued). Results of Monte-Carlo simulations for bromide in pore water at site GA1L.



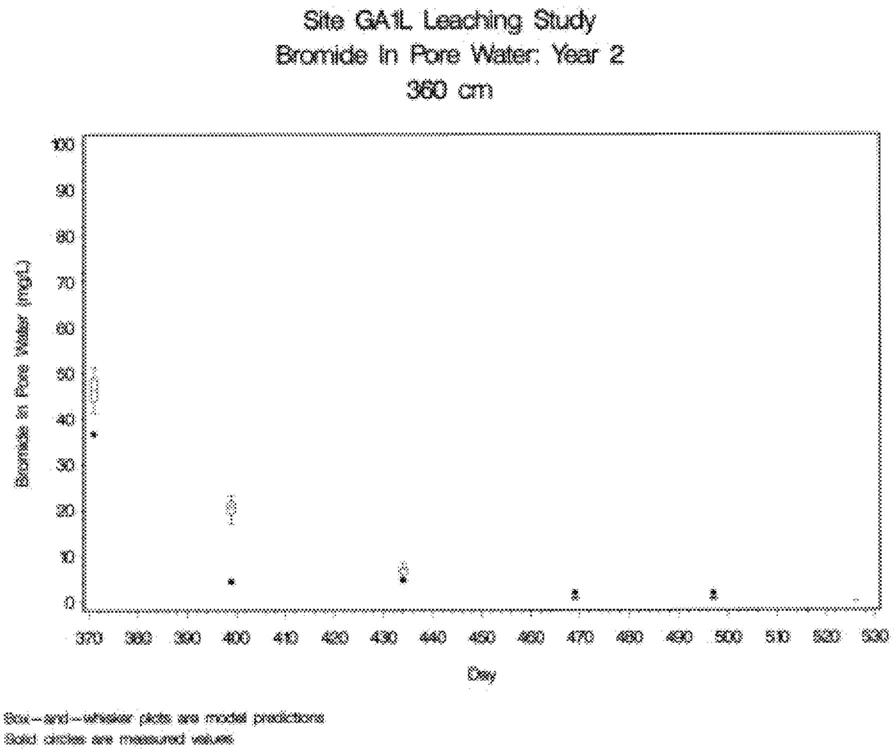
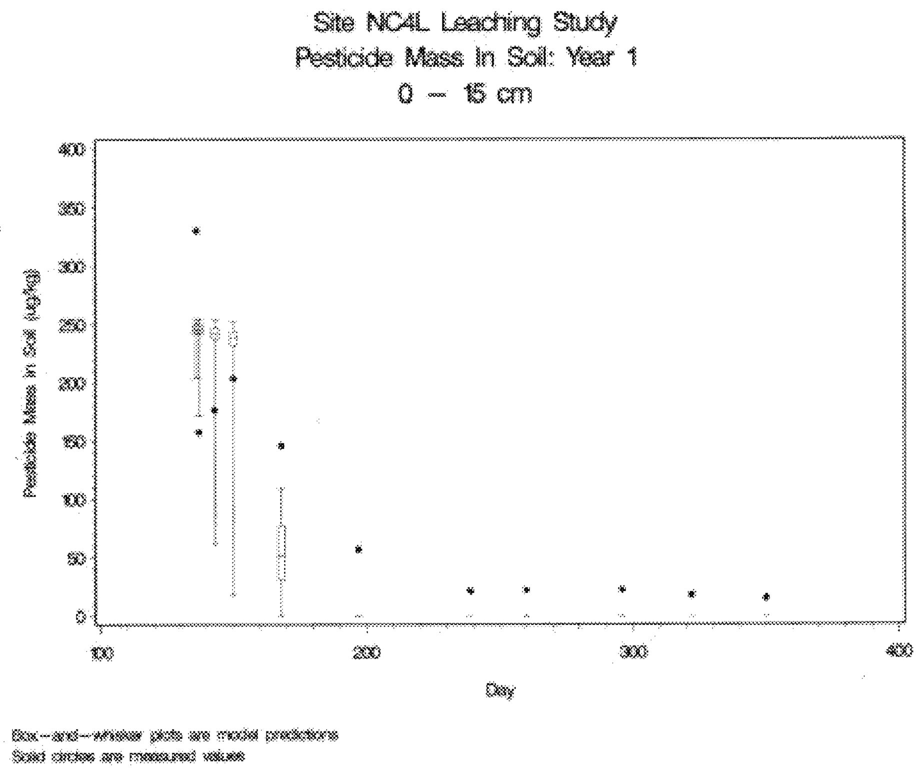


Figure A8-12. Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



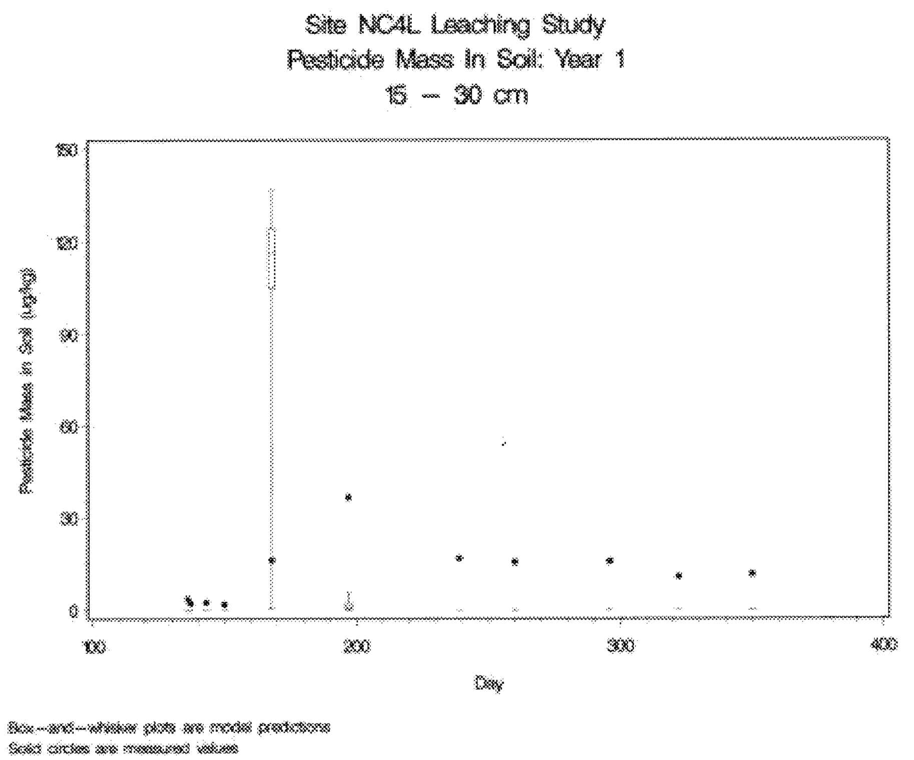
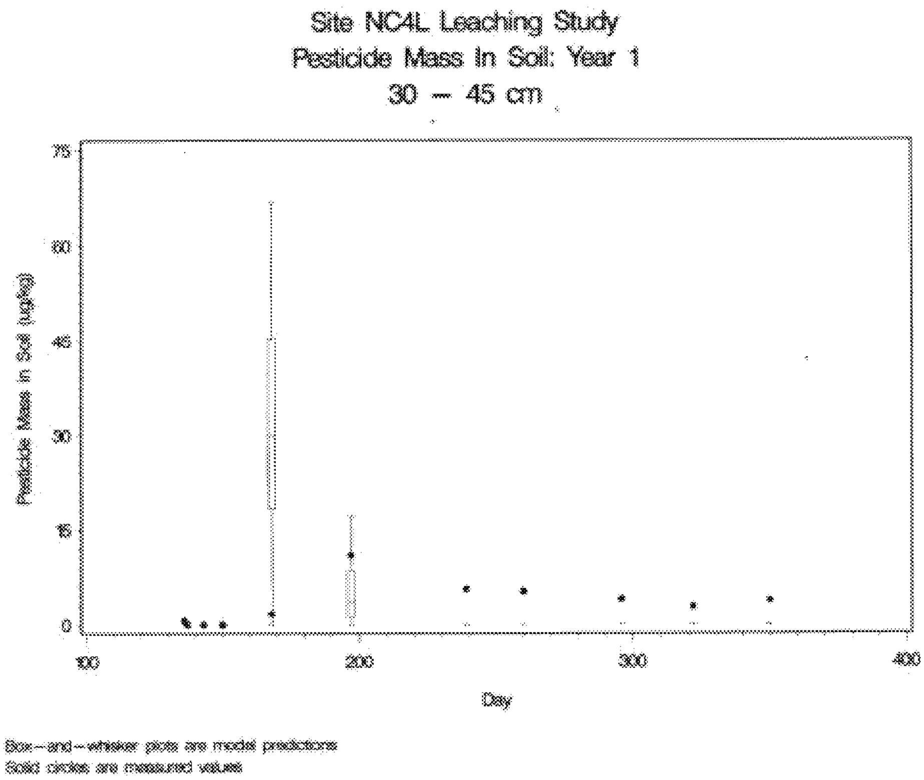


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



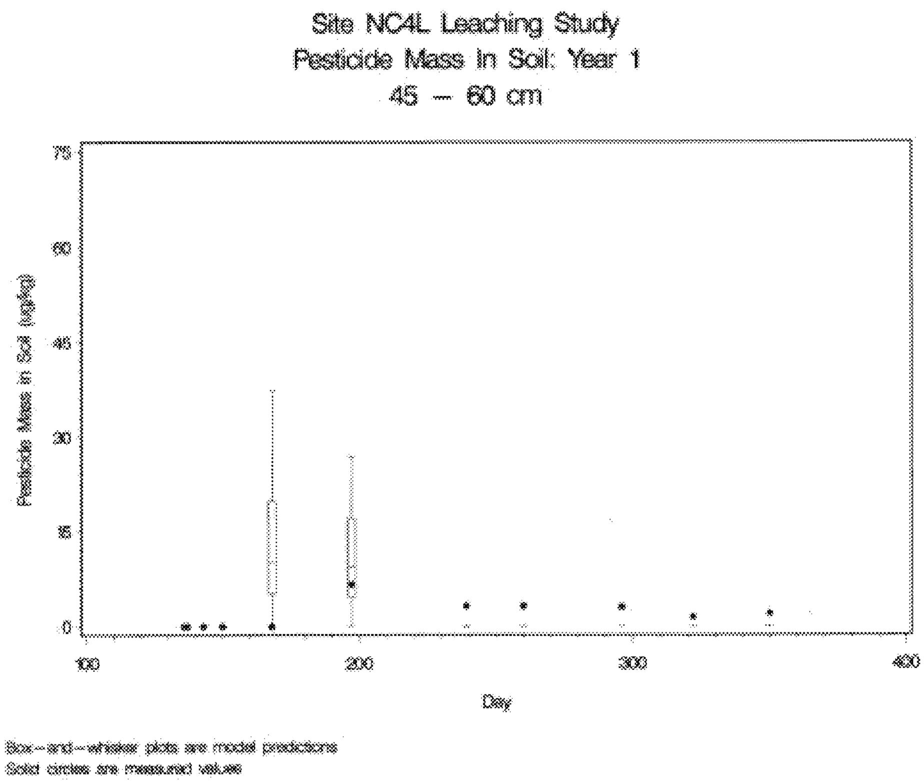
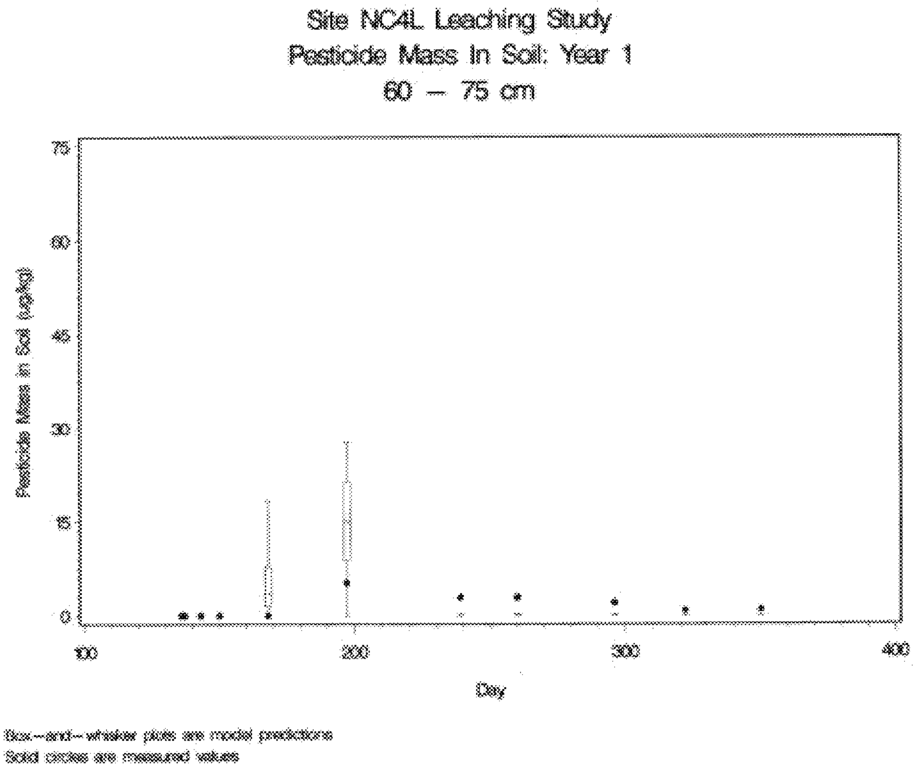


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



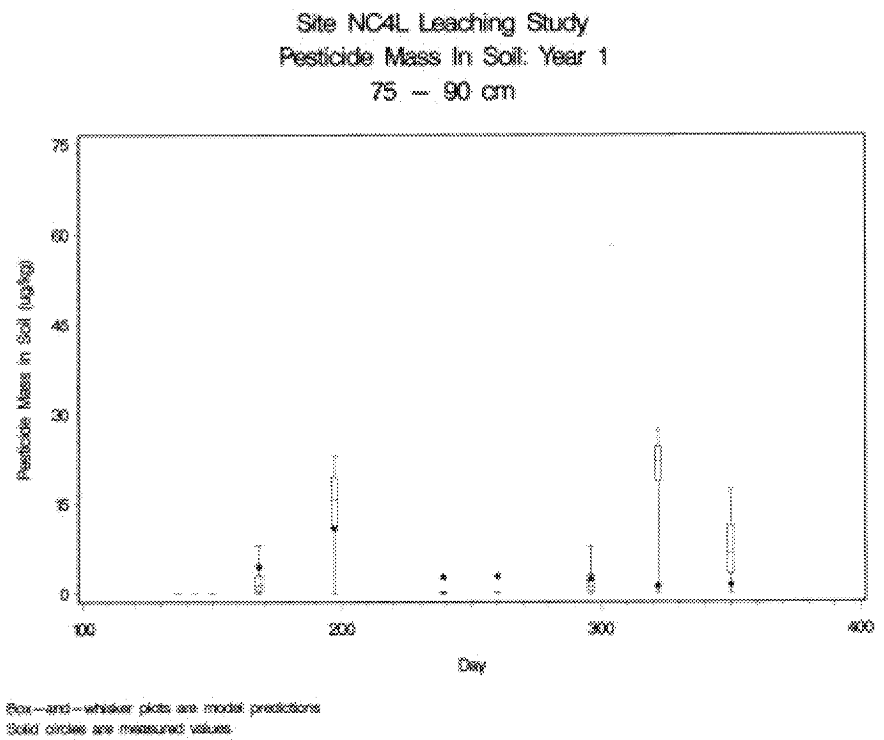
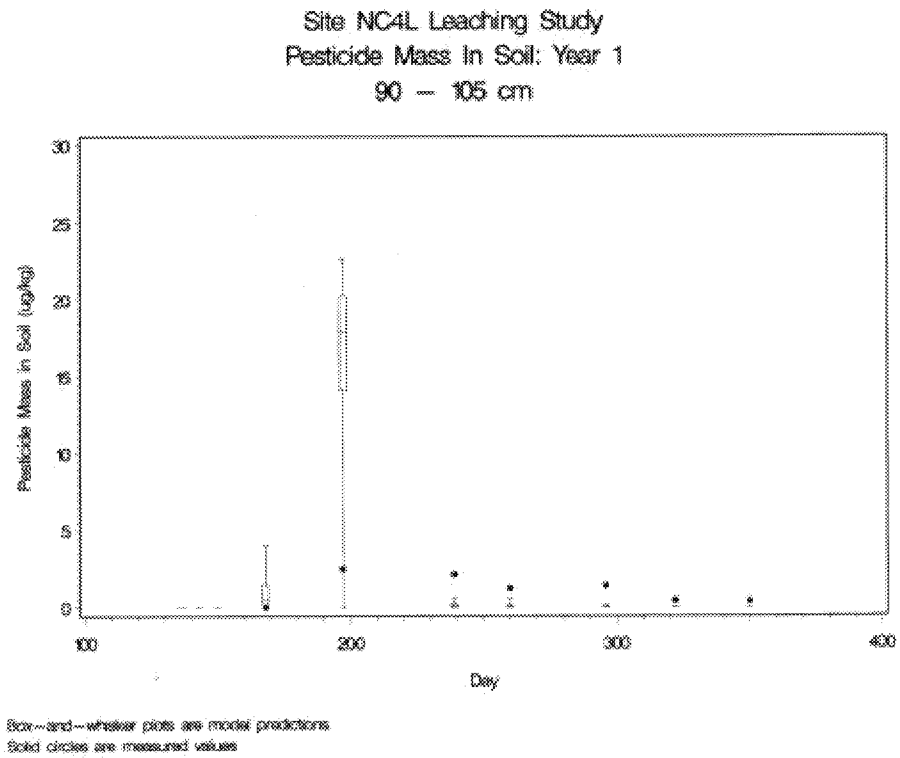


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



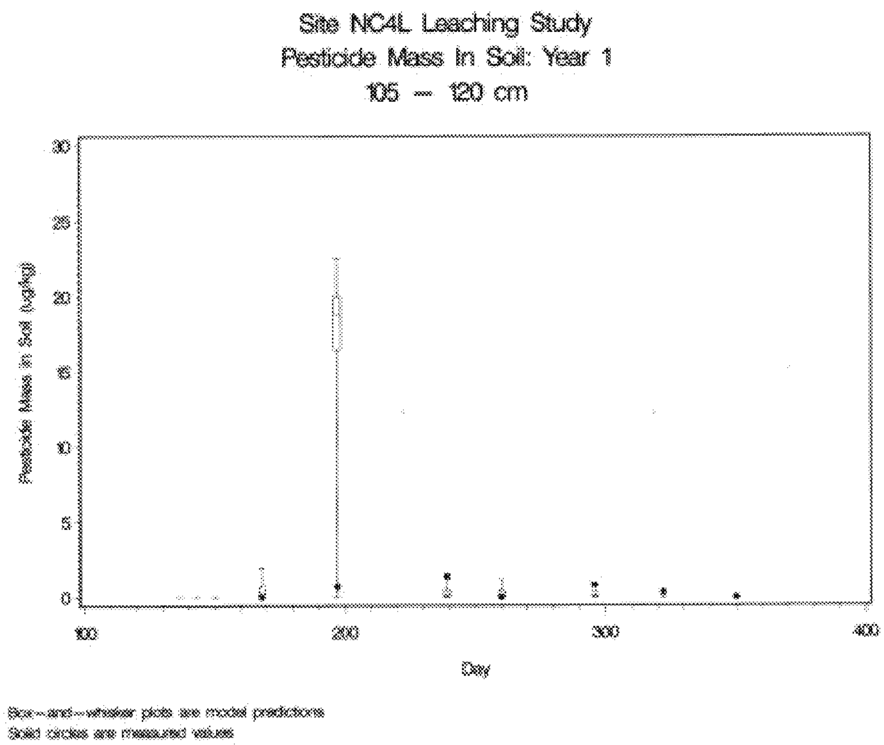
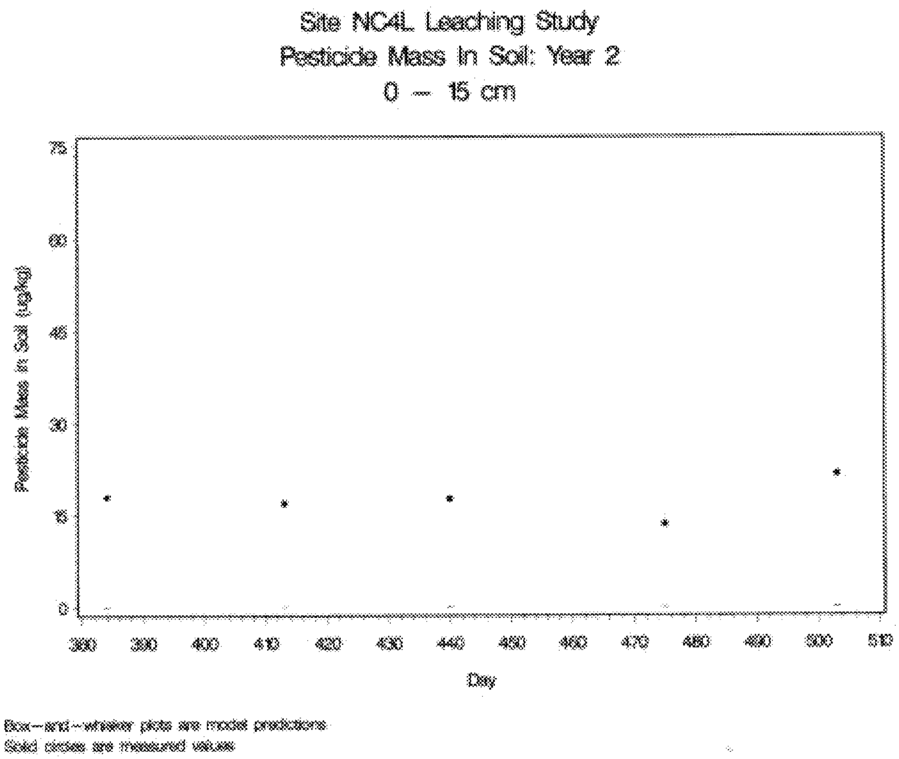


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



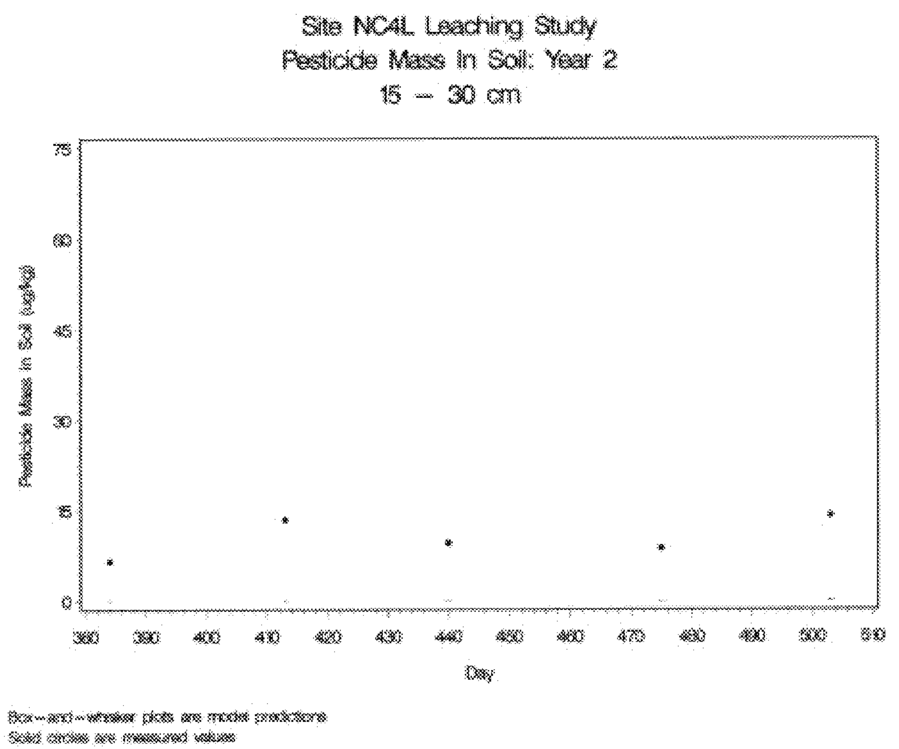
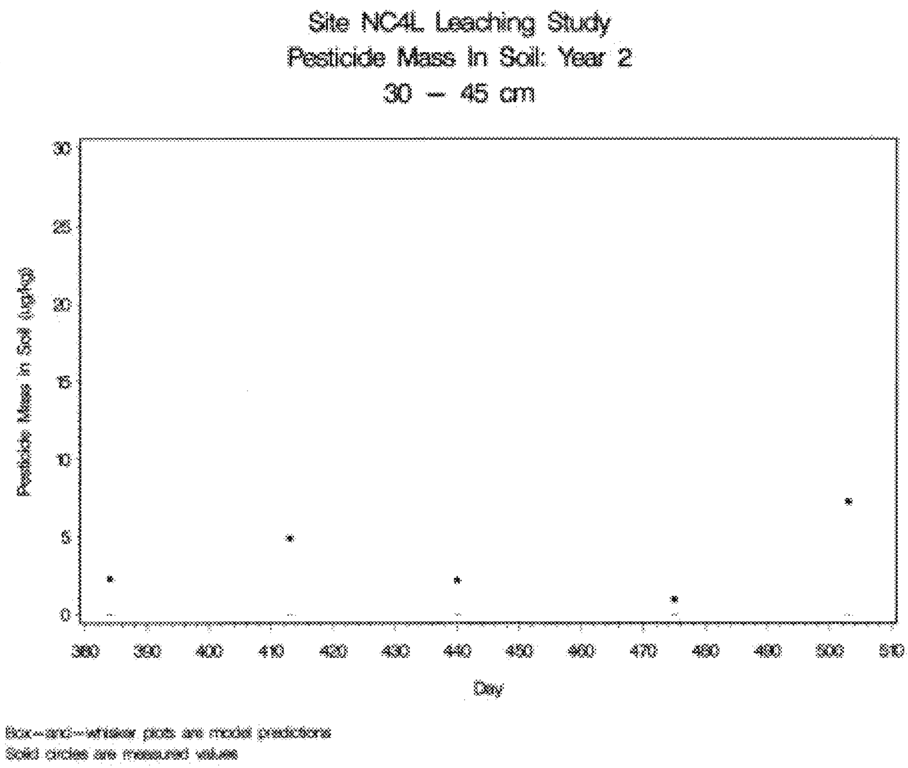


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



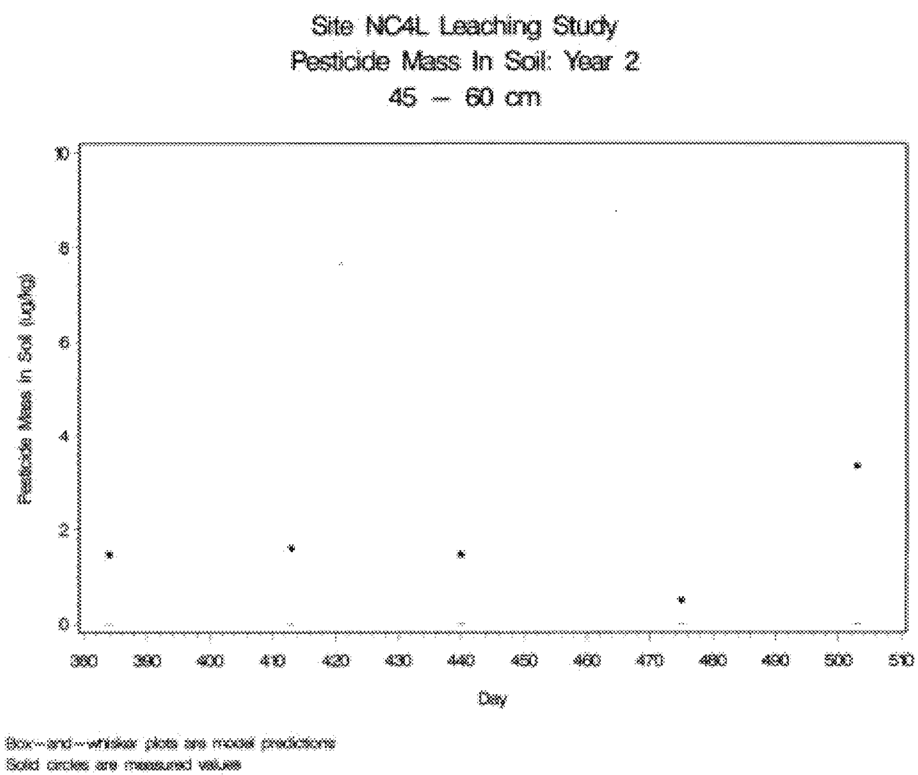
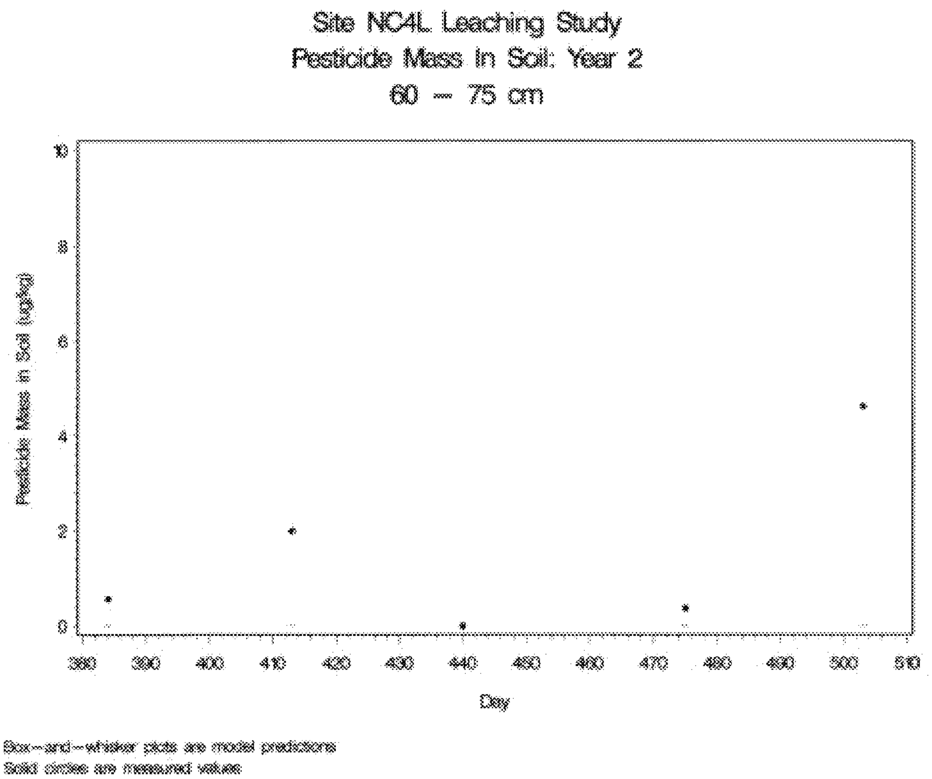


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



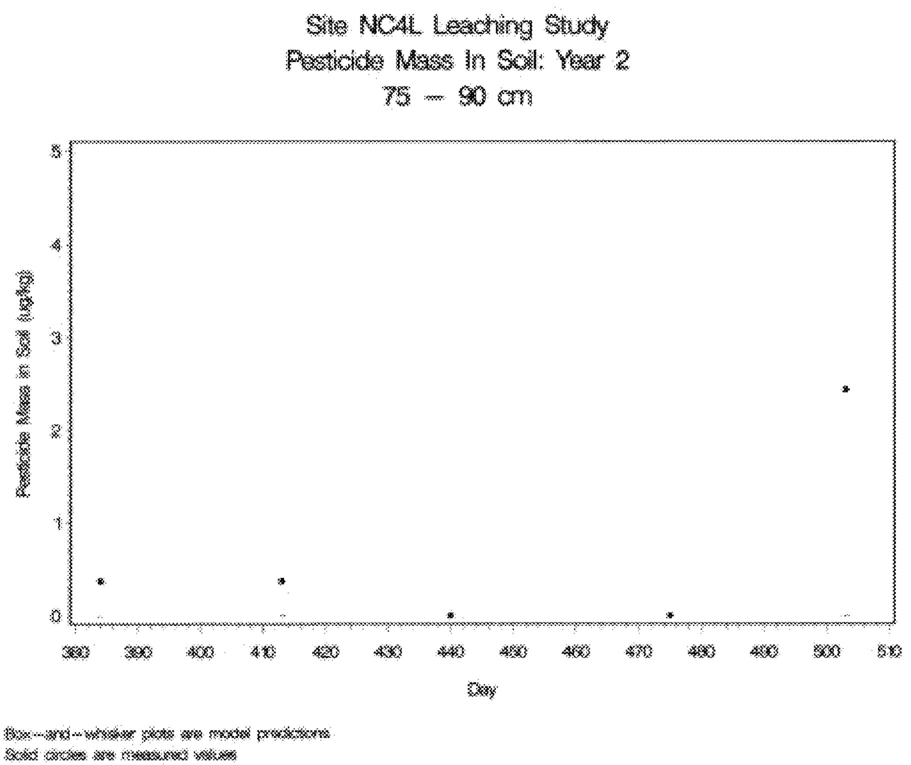
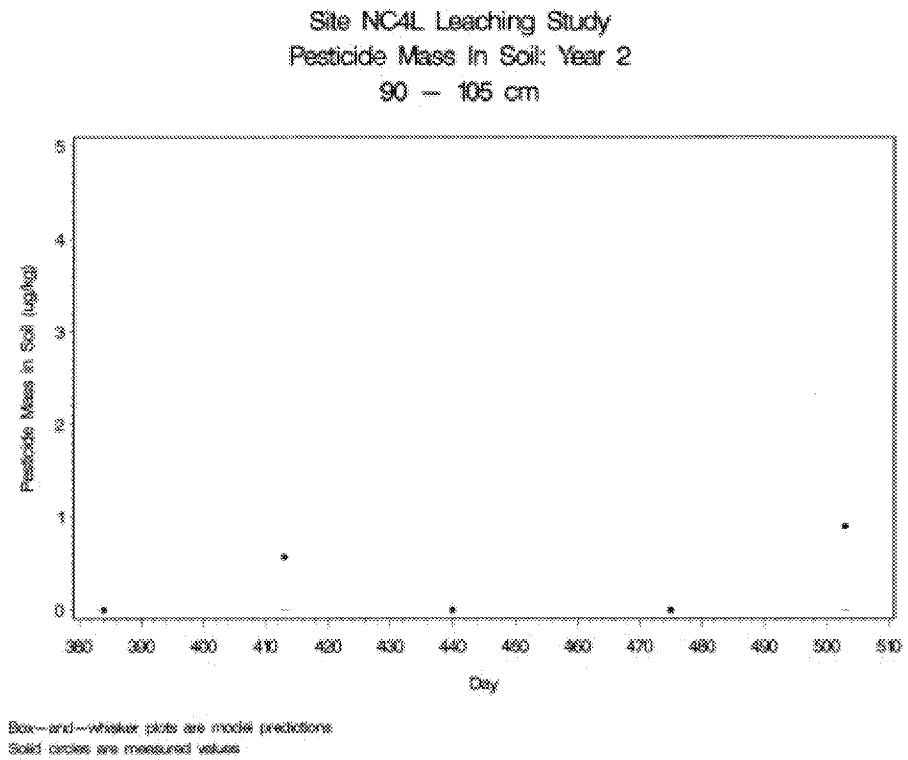


Figure A8-12 (continued). Results of Monte-Carlo simulations for pesticide mass in soil at site NC4L.



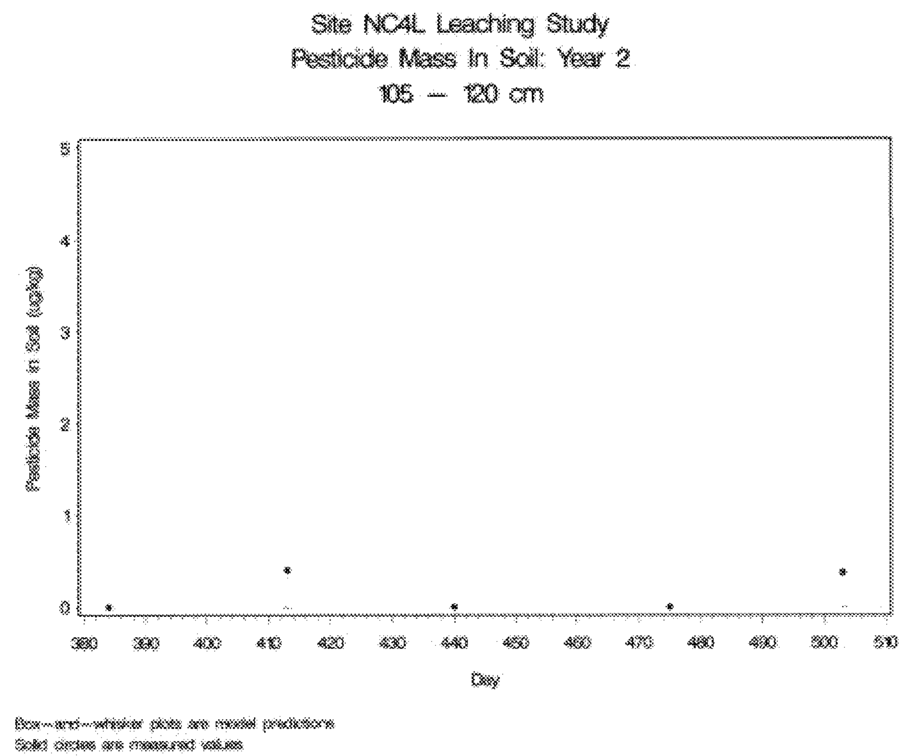
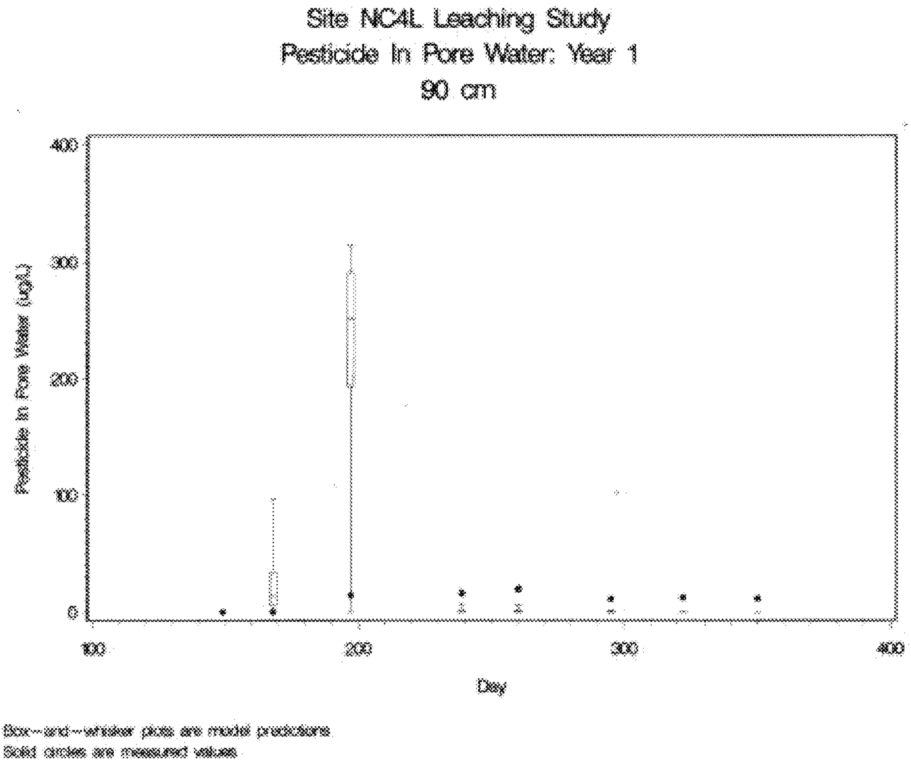


Figure A8-13. Results of Monte-Carlo simulations for pesticide in pore water at site NC4L.



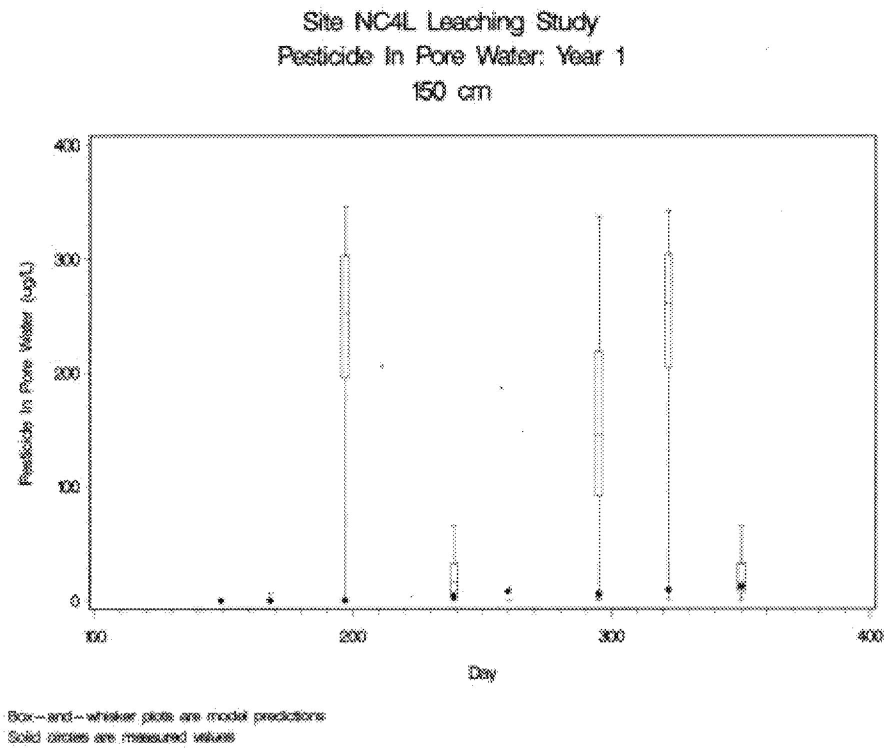
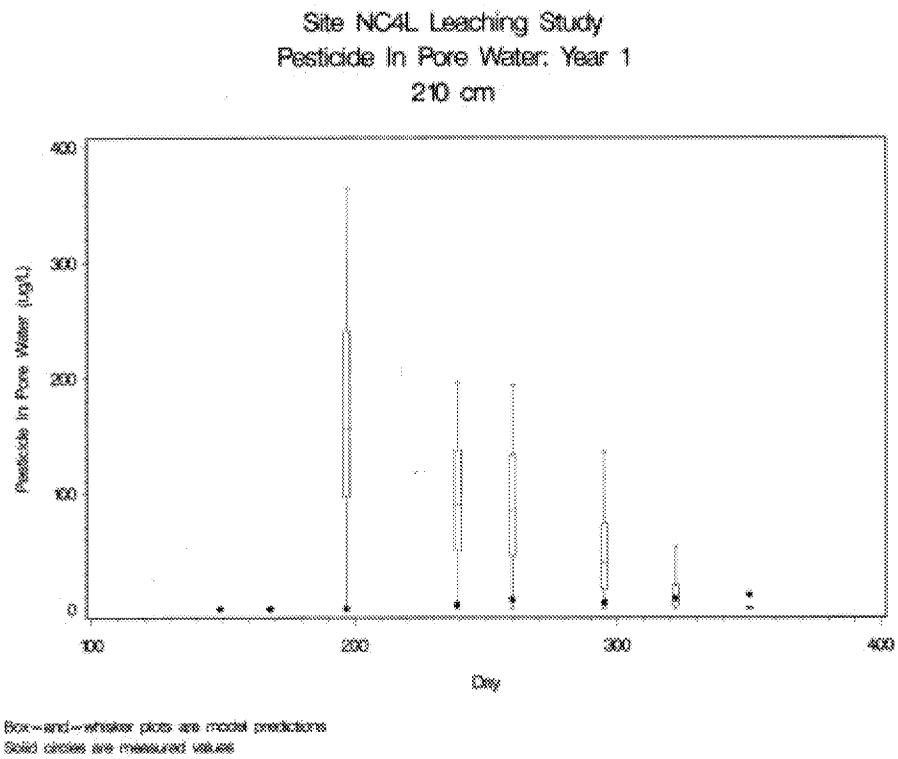


Figure A8-13 (continued). Results of Monte-Carlo simulations for pesticide in pore water at site NC4L.



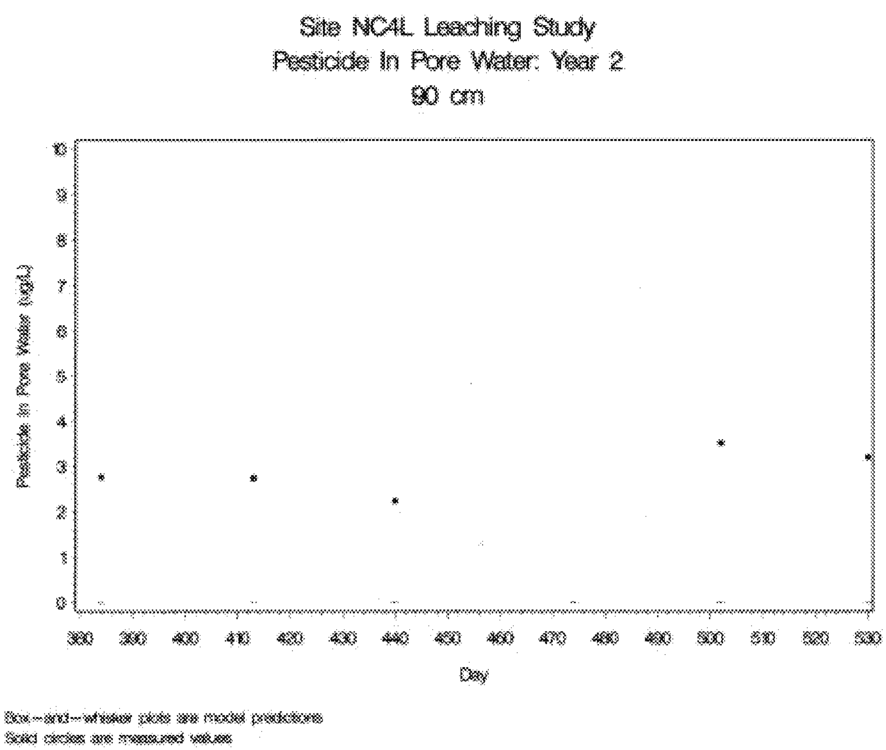
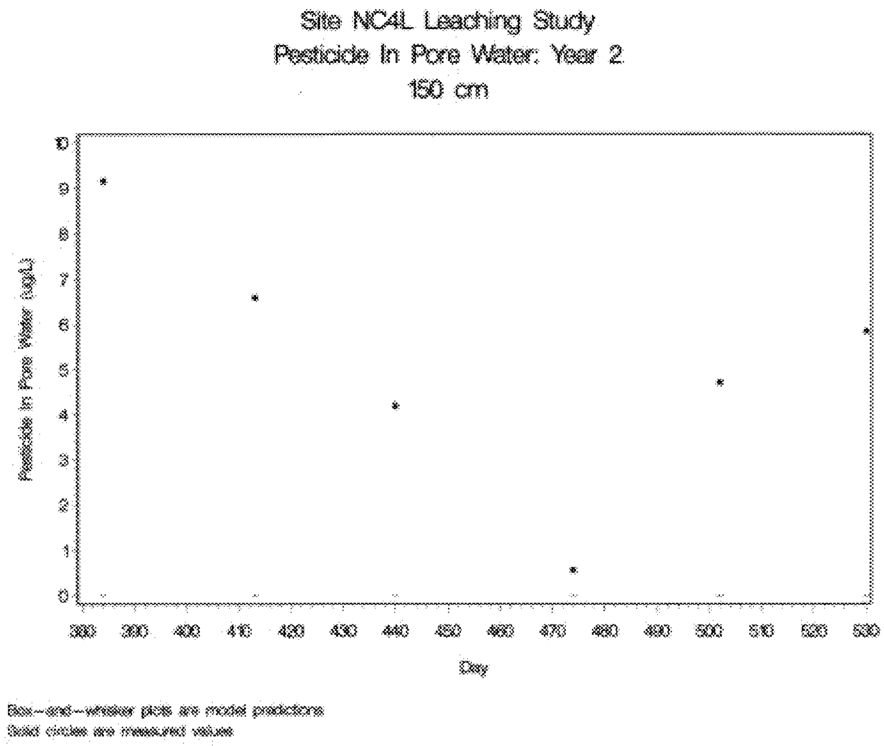


Figure A8-13 (continued). Results of Monte-Carlo simulations for pesticide in pore water at site NC4L.



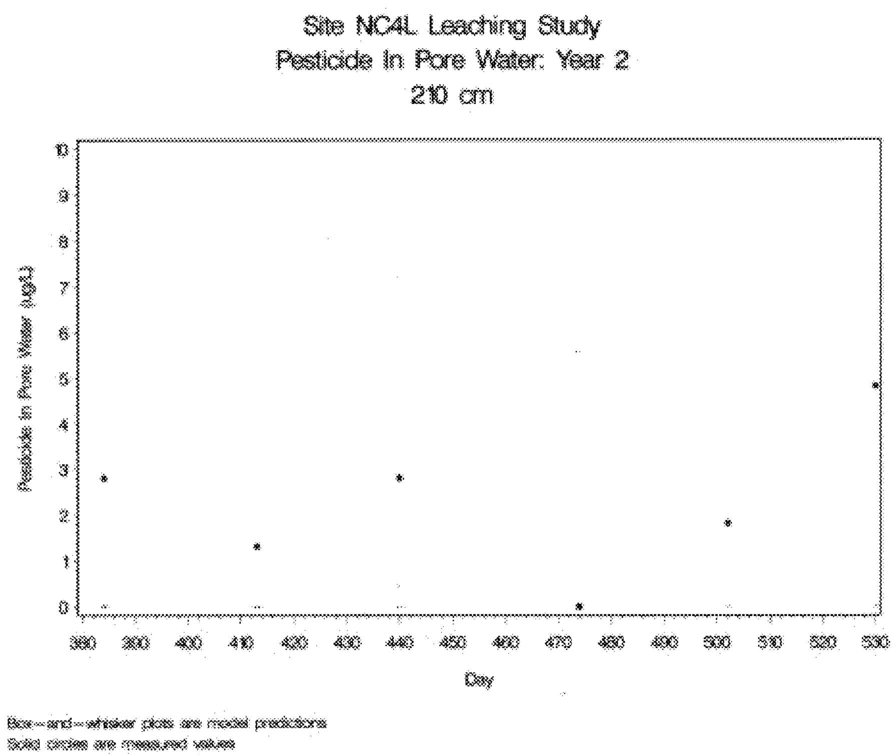
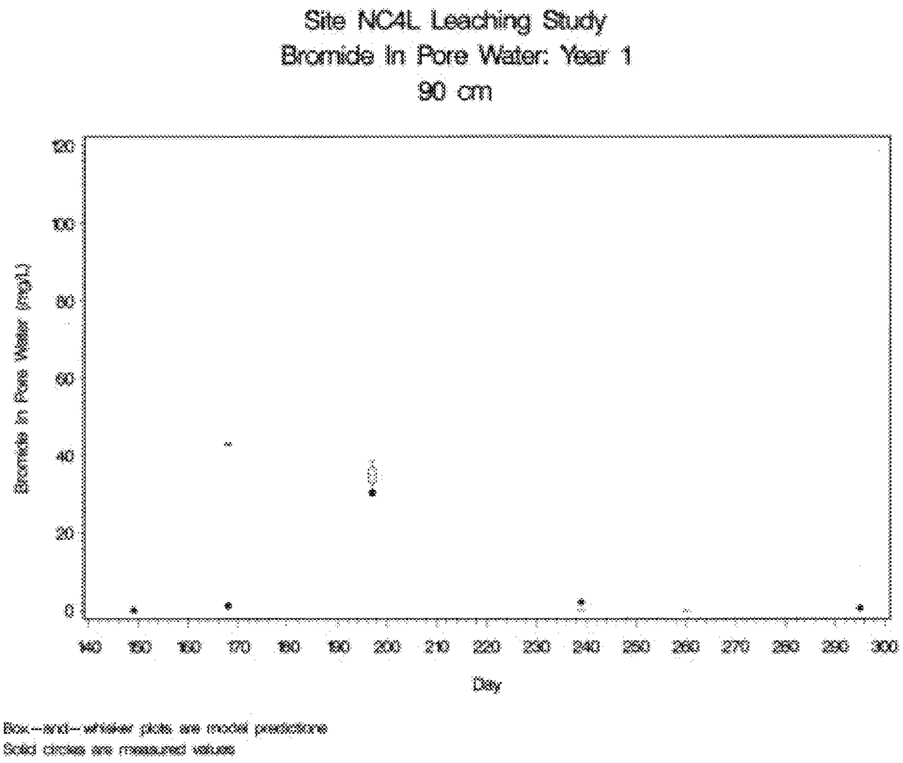


Figure A8-14. Results of Monte-Carlo simulations for bromide in pore water at site NC4L.



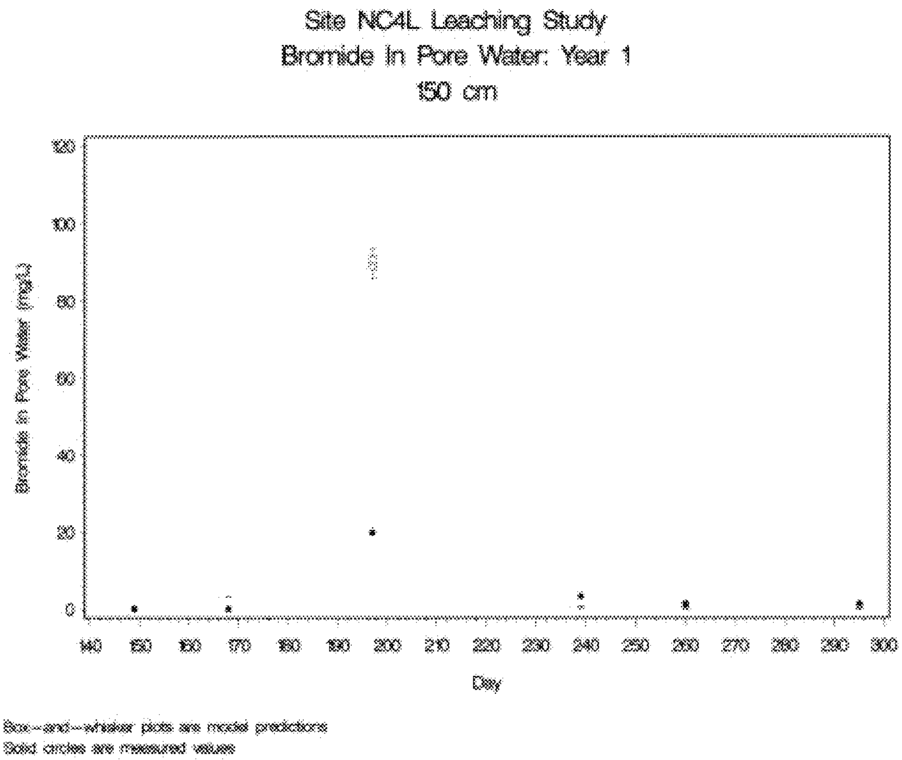


Figure A8-14 (continued). Results of Monte-Carlo simulations for bromide in pore water at site NC4L.

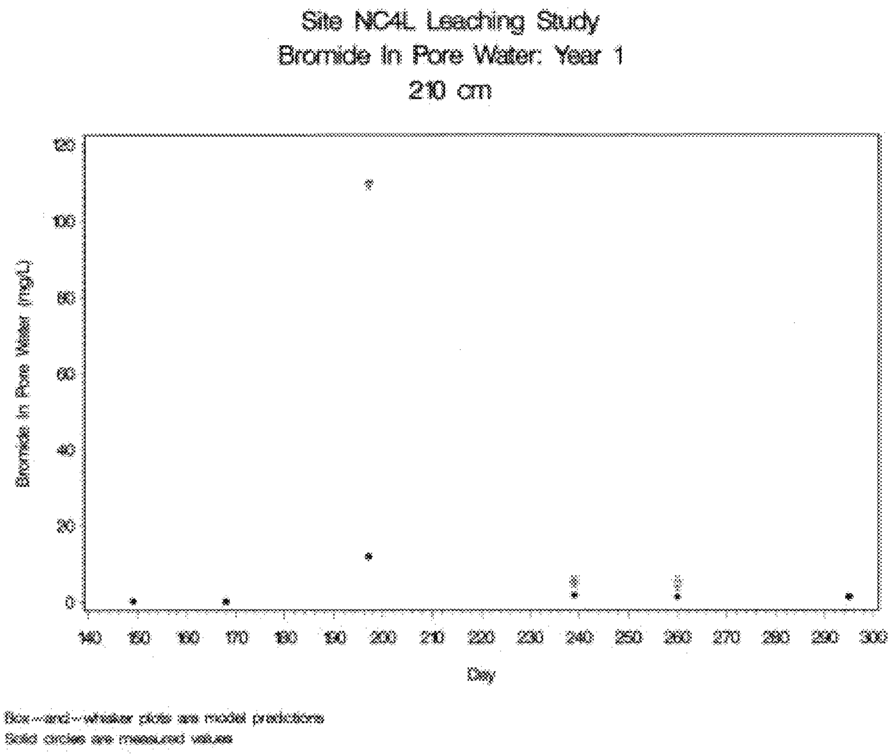


Table A8-1. Daily comparison of model predictions and measured values for IA2R.

Date	Runoff Variables	Measured Values	Percent of Predictions Exceeding the Measured Value (%)
1992: Day 195	Runoff Volume (m^3)	319.2	69.2
	Sediment Yield (kg)	1543	59.6
	Pesticide Runoff Mass (g)	0.330	82.8
	Pesticide Mass in Sediment (g)	1.38	59.6
1992: Day 196	Runoff Volume (m^3)	21.9	38.6
	Sediment Yield (kg)	73.0	30.0
	Pesticide Runoff Mass (g)	0.029	43.8
	Pesticide Mass in Sediment(g)	0.062	34.8
1992: Day 207	Runoff Volume (m^3)	3170.8	53.0
	Sediment Yield (kg)	10022	68.6
	Pesticide Runoff Mass (g)	9.0	67.4
	Pesticide Mass in Sediment(g)	18.9	30.6
1993: Day 169	Runoff Volume (m^3)	688.7	45.0
	Sediment Yield (kg)	16980	0.0
	Pesticide Runoff Mass (g)	0.792	60.6
	Pesticide Mass in Sediment(g)	16.1	0.2
1993: Day 180	Runoff Volume (m^3)	185.7	36.4
	Sediment Yield (kg)	2619	8.2
	Pesticide Runoff Mass (g)	3.270	27.2
	Pesticide Mass in Sediment(g)	26.2	1.0
1993: Day 181	Runoff Volume (m^3)	11.7	36.4
	Sediment Yield (kg)	4208	0.0
	Pesticide Runoff Mass (g)	0.046	38.4

Table A8-1 (continued). Daily comparison of model predictions and measured values for IA2R.

Date	Runoff Variables	Measured Values	Percent of Predictions Exceeding the Measured Value (%)
	Pesticide Mass in Sediment(g)	9.55	0.0
1993: Day 185	Runoff Volume (m^3)	1604.5	40.4
	Sediment Yield (kg)	14272	2.4
	Pesticide Runoff Mass (g)	0.477	94.6
	Pesticide Mass in Sediment(g)	37.0	10.4

Table A8-2. Daily comparison of model predictions and measured values for GA1R.

Date	Runoff Variables	Measured Values	Percent of Predictions Exceeding the Measured Value (%)
1989: Day 220	Pesticide Runoff Mass (g)	3.620	44.8
1989: Day 238	Pesticide Runoff Mass (g)	8.330	60.6
1989: Day 243	Pesticide Runoff Mass (g)	1.320	46.0
1989: Day 274	Pesticide Runoff Mass (g)	0.012	57.0

Table A8-3. Distribution of model predictions for days with no measured values with IA2R.

		Percent of all data with zeros	Value of the Model Prediction At Selected Percentiles				
			25%	50%	75%	90%	95%
Runoff Volume (m^3)	1992	69.00	0.0	0.0	22.1	411.8	979.2
	1993	70.00	0.0	0.0	4.9	238.0	674.3
Sediment Yield (kg)	1992	69.00	0.0	0.0	8.6	646.7	3797.5
	1993	70.00	0.0	0.0	0.8	202.7	1523.0
Pesticide Runoff Mass (g)	1992	70.00	0.0	0.0	0.0	1.0	3.4
	1993	75.00	0.0	0.0	0.0	0.2	1.0
Pesticide Mass in Sediment (g)	1992	74.00	0.0	0.0	0.0	0.2	1.3
	1993	83.00	0.0	0.0	0.0	0.0	0.3

Table A8-4. Distribution of model predictions for days with no measured values with GA1R.

		Percent of all data with zeros	Value of the Model Prediction At Selected Percentiles				
			25%	50%	75%	90%	95%
Pesticide Runoff Mass (g)	1989	78.00	0.0	0.0	0.0	1.0	0.0

Table A8-5. Daily comparison of model predictions and measured values for pesticide mass in soil in Year 1 with GA1L.

Observations	*Day*	*Depth*	*Measured ug/kg*	*Percent Exceedence*
1	226	0-15	67.00	80.2
2	226	15-30	0.50	0.0
3	226	30-45	0.50	0.0
4	226	45-60	na	na
5	236	0-15	40.33	17.4
6	236	15-30	0.50	98.2
7	236	30-45	0.50	68.2
8	236	45-60	na	na
9	237	0-15	122.80	15.4
10	237	15-30	0.50	97.0
11	237	30-45	0.50	65.6
12	237	45-60	na	na
13	246	0-15	35.77	52.8
14	246	15-30	3.53	61.1
15	246	30-45	0.50	47.8
16	246	45-60	0.50	2.6
17	247	0-15	94.33	57.7
18	247	15-30	1.30	73.7
19	247	30-45	0.50	45.9
20	247	45-60	0.50	2.6
21	257	0-15	27.40	60.9
22	257	15-30	0.71	91.1
23	257	30-45	0.50	69.2
24	257	45-60	0.50	43.7
25	258	0-15	102.40	39.5
26	258	15-30	12.33	42.5
27	258	30-45	0.50	68.2
28	258	45-60	0.50	42.7
29	267	0-15	30.50	62.8
30	267	15-30	0.50	78.7
31	267	30-45	0.50	56.1
32	267	45-60	na	na
33	268	0-15	80.93	58.7
34	268	15-30	0.50	76.9
35	268	30-45	0.50	54.7
36	268	45-60	na	na
37	289	0-15	422.00	32.4
38	289	15-30	13.07	81.6
39	289	30-45	0.50	95.7
40	289	45-60	0.50	97.6
41	316	0-15	22.47	59.5
42	316	15-30	2.96	68.8
43	316	30-45	0.50	70.8
44	316	45-60	0.50	78.1
45	343	0-15	10.11	26.7
46	343	15-30	2.18	53.6
47	343	30-45	0.85	55.9
48	343	45-60	0.50	61.1

na. Data not available

Table A8-6. Daily comparison of model predictions and measured values for pesticide mass in soil in Year 2 with GA1L.

Observations	*Day*	*Depth*	*Measured ug/kg*	*Percent Exceedence*
1	371	0-15	5.28	11.6
2	371	15-30	2.96	32.2
3	371	30-45	1.27	36.8
4	371	45-60	0.50	50.0
5	399	0-15	3.91	0.0
6	399	15-30	2.45	9.6
7	399	30-45	0.88	24.8
8	399	45-60	0.75	32.0
9	433	0-15	3.27	0.0
10	433	15-30	1.10	1.6
11	433	30-45	0.50	14.4
12	433	45-60	0.50	21.2
13	468	0-15	3.37	0.0
14	468	15-30	0.94	0.0
15	468	30-45	0.50	2.0
16	468	45-60	0.50	8.8
17	496	0-15	4.96	0.0
18	496	15-30	1.85	0.0
19	496	30-45	0.50	1.4
20	496	45-60	0.50	7.6
21	525	0-15	2.31	0.0
22	525	15-30	0.50	0.0
23	525	30-45	0.50	0.0
24	525	45-60	na	na
25	554	0-15	0.50	0.0
26	554	15-30	0.50	0.0
27	554	30-45	0.50	0.0
28	554	45-60	na	na
29	587	0-15	0.50	0.0
30	587	15-30	0.50	0.0
31	587	30-45	0.50	0.0
32	587	45-60	na	na
33	625	0-15	0.50	0.0
34	625	15-30	0.50	0.0
35	625	30-45	0.50	0.0
36	625	45-60	na	na
37	652	0-15	0.50	0.0
38	652	15-30	0.50	0.0
39	652	30-45	0.50	0.0
40	652	45-60	0.50	0.0

na. Data not available

Table A8-7. Daily comparison of model predictions and measured values for pesticide in pore water in Year 1 with GA1L.

Observations	*Day*	*Depth*	*Measured ug/L*	*Percent Exceedence*
1	236	90	0.05	0.0
2	236	180	0.05	0.0
3	236	270	0.05	0.0
4	236	360	0.05	0.0
5	246	90	0.05	0.0
6	246	180	0.05	0.0
7	246	270	0.05	0.0
8	246	360	0.05	0.0
9	257	90	0.05	0.0
10	257	180	0.05	0.0
11	257	270	0.05	0.0
12	257	360	0.05	0.0
13	267	90	0.05	0.0
14	267	180	0.05	0.0
15	267	270	0.05	0.0
16	267	360	0.05	0.0
17	289	90	0.05	100.0
18	289	180	0.32	0.0
19	289	270	0.08	0.0
20	289	360	0.05	0.0
21	316	90	0.05	100.0
22	316	180	0.05	0.0
23	316	270	0.05	0.0
24	316	360	0.05	0.0
25	343	90	0.05	100.0
26	343	180	0.05	0.0
27	343	270	0.48	0.0
28	343	360	0.05	0.0

Table A8-8. Daily comparison of model predictions and measured values for pesticide in pore water in Year 2 with GA1L.

Observations	*Day*	*Depth*	*Measured ug/L*	*Percent Exceedence*
1	371	90	0.05	100.0
2	371	180	0.05	0.0
3	371	270	0.33	0.0
4	371	360	0.05	0.0
5	399	90	0.12	97.8
6	399	180	0.05	0.0
7	399	270	0.15	0.0
8	399	360	0.05	0.0
9	434	90	0.05	0.0
10	434	180	0.05	0.0
11	434	270	0.17	0.0
12	434	360	0.05	0.0
13	469	90	0.13	0.0
14	469	180	0.05	0.0
15	469	270	0.23	0.0
16	469	360	0.10	0.0
17	497	90	0.30	0.0
18	497	180	0.05	0.0
19	497	270	0.31	0.0
20	497	360	0.16	0.0
21	526	90	0.21	0.0
22	526	180	1.16	0.0
23	526	270	0.25	0.0
24	526	360	0.05	0.0
25	554	90	0.05	0.0
26	554	180	0.38	0.0
27	554	270	0.36	0.0
28	554	360	0.18	0.0

Table A8-9. Daily comparison of model predictions and measured values for bromide in pore water in Year 1 with GA1L.

Observations	*Day*	*Depth*	*Measured mg/L*	*Percent Exceedence*
1	224	90	0.25	0.0
2	224	180	na	na
3	224	270	0.38	0.0
4	236	90	3.58	100.0
5	236	180	0.25	100.0
6	236	270	0.38	0.0
7	247	90	43.42	100.0
8	247	180	15.13	0.0
9	247	270	0.25	0.0
10	258	90	93.33	88.6
11	258	180	25.13	100.0
12	258	270	0.25	100.0
13	268	90	113.30	11.4
14	268	180	30.13	100.0
15	268	270	0.25	100.0
16	289	90	51.20	0.0
17	289	180	68.00	0.0
18	289	270	33.00	100.0
19	316	90	59.00	0.0
20	316	180	27.50	100.0
21	316	270	12.00	100.0
22	344	90	8.37	0.0
23	344	180	30.00	0.0
24	344	270	20.00	100.0
25	371	360	0.05	0.0
26	399	360	0.05	0.0
27	434	360	0.05	0.0
28	463	360	0.10	0.0
29	497	360	0.16	0.0
30	526	360	0.05	0.0
31	554	360	0.18	0.0

na. Data not available

Table A8-10. Daily comparison of model predictions and measured values for bromide in pore water in Year 2 with GA1L.

Observations	*Day*	*Depth*	*Measured mg/L*	*Percent Exceedence*
1	371	90	20.00	0.0
2	371	180	14.00	0.0
3	371	270	9.00	100.0
4	371	360	0.05	0.0
5	399	90	10.00	0.0
6	399	180	12.00	0.0
7	399	270	8.00	0.0
8	399	360	0.05	0.0
9	434	90	2.80	0.0
10	434	180	10.33	0.0
11	434	270	5.50	0.0
12	434	360	0.05	0.0
13	469	90	na	na
14	469	180	6.70	0.0
15	469	270	3.33	0.0
16	469	360	0.10	0.0
17	497	90	1.10	0.0
18	497	180	0.70	0.0
19	497	270	2.83	0.0
20	497	360	0.16	0.0
21	526	90	0.25	0.0
22	526	180	2.50	0.0
23	526	270	2.70	0.0
24	526	360	0.05	0.0
25	554	360	0.18	0.0

na. Data not available

Table A8-11. Daily comparison of model predictions and measured values for pesticide mass in soil in Year 1 with NC4L.

Observations	*Day*	*Depth*	*Measured ug/kg*	*Percent Exceedence*
1	136	0-15	330.30	0.0
2	136	15-30	3.53	0.0
3	136	30-45	0.67	0.0
4	136	45-60	0.00	0.0
5	136	60-75	0.00	0.0
6	136	75-90	na	na
7	136	90-105	na	na
8	136	105-120	na	na
9	137	0-15	157.40	100.0
10	137	15-30	2.23	0.0
11	137	30-45	0.00	0.0
12	137	45-60	0.00	0.0
13	137	60-75	0.00	0.0
14	137	75-90	na	na
15	137	90-105	na	na
16	137	105-120	na	na
17	143	0-15	176.60	98.2
18	143	15-30	2.53	0.0
19	143	30-45	0.00	0.0
20	143	45-60	0.00	0.0
21	143	60-75	0.00	0.0
22	143	75-90	na	na
23	143	90-105	na	na
24	143	105-120	na	na
25	150	0-15	203.50	92.0
26	150	15-30	1.83	0.0
27	150	30-45	0.00	0.0
28	150	45-60	0.00	0.0
29	150	60-75	0.00	0.0
30	150	75-90	na	na
31	150	90-105	na	na
32	150	105-120	na	na
33	168	0-15	145.80	0.0
34	168	15-30	16.17	99.4
35	168	30-45	1.70	99.6
36	168	45-60	0.00	100.0
37	168	60-75	0.00	100.0
38	168	75-90	4.40	13.0
39	168	90-105	0.00	99.8
40	168	105-120	0.00	99.8
41	197	0-15	56.67	0.0
42	197	15-30	36.67	0.0
43	197	30-45	10.93	16.4
44	197	45-60	6.63	62.2
45	197	60-75	5.23	92.6

Table A8-11 (continued). Daily comparison of model predictions and measured values for pesticide mass in soil in Year 1 with NC4L.

Observations	***Day***	***Depth***	***Measured ug/kg***	***Percent Exceedence***
46	197	75-90	10.83	76.0
47	197	90-105	2.50	98.2
48	197	105-120	0.70	99.6
49	239	0-15	21.00	0.0
50	239	15-30	16.77	0.0
51	239	30-45	5.60	0.0
52	239	45-60	3.20	0.0
53	239	60-75	2.87	0.0
54	239	75-90	2.73	0.0
55	239	90-105	2.13	0.0
56	239	105-120	1.37	0.0
57	260	0-15	21.97	0.0
58	260	15-30	15.60	0.0
59	260	30-45	5.23	0.0
60	260	45-60	3.20	0.0
61	260	60-75	2.90	0.0
62	260	75-90	2.87	0.0
63	260	90-105	1.23	0.0
64	260	105-120	0.00	98.4
65	296	0-15	22.03	0.0
66	296	15-30	15.80	0.0
67	296	30-45	4.00	0.0
68	296	45-60	3.03	0.0
69	296	60-75	2.03	0.0
70	296	75-90	2.37	30.2
71	296	90-105	1.40	0.0
72	296	105-120	0.80	0.0
73	322	0-15	17.87	0.0
74	322	15-30	10.83	0.0
75	322	30-45	2.83	0.0
76	322	45-60	1.43	0.0
77	322	60-75	0.73	0.0
78	322	75-90	1.27	99.6
79	322	90-105	0.43	0.0
80	322	105-120	0.33	0.0
81	350	0-15	15.10	0.0
82	350	15-30	11.57	0.0
83	350	30-45	3.77	0.0
84	350	45-60	2.00	0.0
85	350	60-75	0.90	0.0
86	350	75-90	1.47	94.0
87	350	90-105	0.37	0.0
88	350	105-120	0.00	100.0

na. Data not available

Table A8-12. Daily comparison of model predictions and measured values for pesticide mass in soil in Year 2 with NC4L

Observations	*Day*	*Depth*	*Measured ug/kg*	*Percent Exceedence*
1	384	0-15	17.90	0.0
2	384	15-30	6.53	0.0
3	384	30-45	2.30	0.0
4	384	45-60	1.47	0.0
5	384	60-75	0.57	0.0
6	384	75-90	0.37	0.0
7	384	90-105	0.00	99.8
8	384	105-120	0.00	99.8
9	413	0-15	16.87	0.0
10	413	15-30	13.43	0.0
11	413	30-45	4.87	0.0
12	413	45-60	1.60	0.0
13	413	60-75	2.00	0.0
14	413	75-90	0.37	0.0
15	413	90-105	0.57	0.0
16	413	105-120	0.40	0.0
17	440	0-15	17.57	0.0
18	440	15-30	9.60	0.0
19	440	30-45	2.20	0.0
20	440	45-60	1.47	0.0
21	440	60-75	0.00	66.4
22	440	75-90	0.00	82.8
23	440	90-105	0.00	98.6
24	440	105-120	0.00	99.8
25	475	0-15	13.43	0.0
26	475	15-30	8.80	0.0
27	475	30-45	0.97	0.0
28	475	45-60	0.50	0.0
29	475	60-75	0.37	0.0
30	475	75-90	0.00	43.0
31	475	90-105	0.00	61.4
32	475	105-120	0.00	77.6
33	503	0-15	21.50	0.0
34	503	15-30	14.10	0.0
35	503	30-45	7.25	0.0
36	503	45-60	3.35	0.0
37	503	60-75	4.63	0.0
38	503	75-90	2.43	0.0
39	503	90-105	0.90	0.0
40	503	105-120	0.37	0.0

Table A8-13. Daily comparison of model predictions and measured values for pesticide in pore water in Year 1 with NC4L

Observations	***Day***	***Depth***	***Measured (ug/L)***	***Percent Exceedence***
1	149	90	0.00	0.0
2	149	150	0.00	0.0
3	149	210	0.00	0.0
4	168	90	0.00	100.0
5	168	150	0.00	99.8
6	168	210	0.00	71.4
7	197	90	14.44	99.2
8	197	150	0.50	99.8
9	197	210	0.25	99.8
10	239	90	15.98	0.0
11	239	150	11.69	57.8
12	239	210	3.65	98.8
13	260	90	19.70	0.0
14	260	150	12.57	0.0
15	260	210	8.00	97.8
16	295	90	11.21	0.0
17	295	150	7.26	99.6
18	295	210	5.40	96.8
19	322	90	12.34	0.0
20	322	150	15.05	99.2
21	322	210	9.22	48.4
22	350	90	11.58	0.0
23	350	150	6.44	75.2
24	350	210	12.25	0.0

Table A8-14. Daily comparison of model predictions and measured values for pesticide in pore water in Year 2 with NC4L

Observations	*Day*	*Depth*	*Measured (ug/L)*	*Percent Exceedence*
1	384	90	2.77	0.0
2	384	150	9.16	0.0
3	384	210	2.81	0.0
4	413	90	2.74	0.0
5	413	150	6.59	0.0
6	413	210	1.32	0.0
7	440	90	2.24	0.0
8	440	150	4.19	0.0
9	440	210	2.81	0.0
10	474	90	na	na
11	474	150	0.56	0.0
12	474	210	0.00	100.0
13	502	90	3.52	0.0
14	502	150	4.71	0.0
15	502	210	1.82	0.0
16	530	90	3.20	0.0
17	530	150	5.85	0.0
18	530	210	4.83	0.0

na. Data not available

Table A8-15. Daily comparison of model predictions and measured values for bomide in pore water in Year 1 with NC4L

Observations	***Day***	***Depth***	***Measured mg/L***	***Percent Exceedence***
1	149	90	0.09	0.0
2	149	150	0.11	0.0
3	149	210	0.12	0.0
4	168	90	1.18	100.0
5	168	150	0.07	100.0
6	168	210	0.09	100.0
7	197	90	30.28	100.0
8	197	150	19.82	100.0
9	197	210	11.86	100.0
10	239	90	2.09	0.0
11	239	150	3.39	0.0
12	239	210	1.72	100.0
13	260	90	na	na
14	260	150	1.38	0.0
15	260	210	1.28	100.0
16	295	90	0.54	0.0
17	295	150	1.34	0.0
18	295	210	1.16	62.6

na. Data not available